Modelling serendipity in a computational context

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Abstract Building on a survey of previous theories of serendipity and creativity, we advance a model of serendipitous occurrences, and a definition of the serendipity potential of a system. Practitioners can use these theoretical tools to evaluate a computational system’s potential for unexpected behaviour that may have a beneficial outcome. In addition to a quantitative rating of serendipity potential – which is computed in terms of population-based estimates of chance, curiosity, sagacity, and value – the model also includes qualitative features that can guide development work. We show how the model is used in three case studies of existing and hypothetical systems, in the context of evolutionary computing, automated programming, and (next-generation) recommender systems. From this analysis, we extract recommendations for practitioners working with computational serendipity, and outline future directions for research.

Keywords serendipity, computational creativity, autonomous systems, evolutionary computing, automated programming, recommender systems

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1 Introduction

The operationalisation of serendipity in computational systems presents a tantalising possibility: for example, by deploying machine learning techniques for pattern recognition, “Instead of waiting for the happy accidents in the lab, you might be able to find them in the data” (Kennedy 2016, p. 70). However – notwithstanding the important advances in data science that lie behind that quote – the idea of computational serendipity remains contentious. The most straightforward view on the matter is what Turing (1950) called “Lovelace’s Objection”: namely, that a computer “can do whatever we know how to order it to perform” (Lovelace 1842, p. 722) – and no more. Lovelace’s Objection has more recently been echoed by one of the foremost scholars of serendipity, Pek van Andel:

“Like all intuitive operating, pure serendipity is not amenable to generation by a computer. The very moment I can plan or programme ‘serendipity’ it cannot be called serendipity anymore.” (van Andel 1994, p. 646)

On the other side of the argument, Minsky (1967) suggests that any sufficiently complex computational system is bound to make decisions that its creators could not foresee, and may not fully understand. In this paper, we aim to theorise serendipity in computational systems, and show that computational systems can have greater or lesser potential for serendipity.

Notions of serendipity are increasingly relevant in the arts, in technology, and elsewhere (McKay 2012; Rao 2015; Kennedy 2016). Serendipity may be encouraged with methods drawn from various domains, including architecture, data science, and cultural engineering. However, these applied approaches tend to be ad hoc, foregoing systematic investigation into the best ways to encourage serendipity. Indeed, in line with the objections sketched above, the question remains as to whether a systematic approach to serendipity is even possible. Computational thinking around this question promises further illumination.

Most previous research on serendipity in a computing context focuses on stimulating serendipitous discovery on the user side. Paul André et al (2009) previously proposed a two-part model of serendipity encompassing “the chance encountering of information, and the sagacity to derive insight from the encounter.” The first phase is the one that is automated most frequently. The SerenA system developed by Deborah Maxwell et al (2012) offers a case study in this phenomenon, which could be called serendipity as a service. The SerenA project aimed to support users in forming bridging connections from an unexpected encounter to a previously unanticipated but valuable outcome. In this paper, by contrast, rather than revisiting the topic of serendipitous discoveries on the user side which are triggered by a computational system, we focus on on modelling serendipity on the system side. We develop a model, associate evaluation criteria, and offer practical guidance for system designers seeking to maximise the potential for serendipity in their systems.

Prior explorations have typically focused on engineering – and in some cases aesthetics (Reichardt 1968) – rather than on theory. Attempts to develop a
more systematic treatment of serendipity include the work of Figueiredo and Campos (2001), who describe several types of serendipitous “moves” that effect the transformation of a problem that cannot be solved into one that can. André et al (2009) suggest that sagacity and insight in computational systems can be improved with added domain expertise and a common language model. While these suggestions are independently valuable, they miss a degree of theoretical unity. For example, recognising new patterns and defining new problems seems to be an important part of many classic examples of serendipity, but this is considerably more ambitious than problem solving. Here, one can compare von Foerster’s (1979 2003) notion of a second-order cybernetics, which theorises system participants who specify their own purpose. Similarly, many historical examples of serendipity are centred on learning, rather than simply reasoning from something that is already known. Louis Pasteur, who is known for several lucky experiments (Roberts 1989; Gaughan 2010), famously remarked: “Dans les champs de l’observation le hasard ne favorise que les esprits préparés” (“In the fields of observation chance favors only the prepared mind”) (Pasteur [1854] 1939, p. 131). Even so, it is not clear that the presence or absence of talents like domain expertise and linguistic ability allow us to draw a distinction between serendipitous and non-serendipitous discovery. Lawley and Tompkins (2008) develop a well articulated process model of serendipity as a sequence of events, and Makri and Blandford (2012a) adapt this to focus on connections amongst data. Our model takes inspiration from an earlier engagement with these approaches (Pease et al 2013) and makes the application to computational systems more systematic.

When we consider classic examples of serendipity, such as the practical uses for weak glue, the possibility that a life-saving antibiotic could be found growing on contaminated petri dishes, or the idea that burdock burrs could be anything but annoying, we notice radical changes in evaluation. Our approach to serendipity centres on a previously unanticipated “focus shift.” We consequently share van Andel’s view that serendipity cannot be planned or programmed: being unanticipated, this shift in focus cannot be predetermined; furthermore, results following a focus shift cannot be guaranteed. However, we suggest that a computational system can be designed to have greater or lesser potential for serendipitous discoveries. Evaluation and reevaluation are key aspects of our approach. For example, asking what weak glue could possibly be useful for might kick off an exploratory process of invention. A system that can detect previously missed opportunities and false realisations – what van Andel (1994, p. 639) terms negative serendipity – may be able to learn from them. The paper focuses on the analysis of several existing and hypothetical systems, in which we (heuristically) map system features to the components of our model. The primary limitation of our model is that it produces contextual or subjective judgements of serendipity potential, which depend on assumptions of the evaluator. Making these assumptions explicit is one of the ways in which the model can be useful as a design and evaluation tool, as our case studies show. More work is needed to realise systems that fully meet the model’s criteria. We include pointers in this direction in the final sections.
Summary of contributions

- We summarise the logical structure of serendipitous occurrences in Section 2, drawing on a brief review of prior literature on the concept of “serendipity,” with reference to the related concepts of “creativity,” “discovery,” and “invention.”
- In Section 3, we synthesise the understanding gained in the previous section in a process-oriented model and definition of the serendipity potential of a system.
- We provide a demonstration of our model and evaluation procedure in Section 4, via three case studies in evolutionary jazz improvisation, automated programming, and next-generation recommender systems.
- Section 5 concludes the paper with recommendations for researchers working on computational serendipity.

2 The structure of serendipitous occurrences: a review of the literature

2.1 Etymology and selected definitions

The English term “serendipity” derives from Horace Walpole’s interpretation of the first chapter of the 1302 poem *Eight Paradises*, in an Italian translation from the Persian of the Sufi poet Amir Khusrow. The term is first found in a 1757 letter from Walpole to Horace Mann:

“This discovery is almost of that kind which I call serendipity, a very expressive word . . . You will understand it better by the derivation than by the definition. I once read a silly fairy tale, called The Three Princes of Serendip: as their Highness travelled, they were always making discoveries, by accidents & sagacity, of things which they were not in quest of.” (van Andel (1994, p. 633); cf. Remer (1965))

Following Walpole’s coinage, “serendipity” was mentioned in print only 135 times over the next 200 years, according to a survey carried out by Robert Merton and Elinor Barber, collected in *The Travels and Adventures of Serendipity* (Merton and Barber 2004). Merton describes his own understanding of a generalised “serendipity pattern” and its constituent parts as follows:

“The serendipity pattern refers to the fairly common experience of observing an unanticipated, anomalous and strategic datum which becomes the occasion for developing a new theory or for extending an existing theory.” (Merton 1948, p. 506) [emphasis in original]

In 1986, Philippe Quéau described serendipity as “the art of finding what we are not looking for by looking for what we are not finding” (Quéau (1986), in the translation of Campos and Figueiredo (2002, p. 121)). Campbell (2005) defines it as “the rational exploitation of chance observation, especially in the
discovery of something useful or beneficial.” Van Andel (1994, p. 631) describes it simply as “the art of making an unsought finding.”

Roberts (1989, pp. 246–249) records 30 entries for the term “serendipity” from English language dictionaries dating from 1909 to 1989. While classic definitions required an accidental discovery, this criterion was modified or omitted later on. Roberts gives the name pseudoserendipity to “sought findings” in which a desired discovery nevertheless follows from an accident. Makri and Blandford (2012a, b) point to a continuum between sought and unsought findings, and highlight the role of subjectivity both in bringing about a serendipitous outcome, and in describing a given sequence of events as “serendipitous.” Many of Roberts’s collected definitions treat serendipity as a psychological attribute: a “gift” or “faculty.” Along these lines, Jonathan Zilberg asserts:

“Chance is an event while serendipity is a capability dependent on bringing separate events, causal and non-causal together through an interpretive experience put to strategic use.” (Zilberg 2015, p. 79)

Numerous historical examples exhibit features of serendipity and involve interpretive frameworks that are deployed on a social rather than on an individual scale. For instance, between Spencer Silver’s creation of high-tack, low-adhesion glue in 1968, Arthur Fry’s invention of a sticky bookmark in 1973, and the eventual launch of the distinctive canary yellow re-stickable notes in 1980, there were many opportunities for Post-it™ not to have come to be (Flavell-While 2012). Merton and Barber argue that a psychological perspective needs to be integrated with a sociological perspective.

“For if chance favours prepared minds, it particularly favours those at work in microenvironments that make for unanticipated sociocognitive interactions between those prepared minds. These may be described as serendipitous sociocognitive microenvironments.” (Merton and Barber 2004, p. 259–260)

Large-scale scientific and technical projects generally rely on the convergence of interests of key actors and various other cultural factors. For example, Umberto Eco (2013) describes the historical role of serendipitous mistakes, falsehoods, and rumours in the production of knowledge.

2.2 Theories of serendipity and creativity

Serendipity is typically discussed in the context of discovery. In everyday parlance, this concept is often linked with invention or creativity (Jordanous and Keller 2012). However, Henri Bergson drew the following distinction:

“Discovery, or uncovering, has to do with what already exists, actually or virtually; it was therefore certain to happen sooner or later. Invention gives being to what did not exist; it might never have happened.” (Bergson [1941] 1946, p. 58)
We suggest that serendipity should be understood in terms of both discovery and invention: that is, the discovery of something unexpected in the world and the invention of an application for the same. Indeed, these terms provide convenient labels for the two-part model describing the “chance encountering of information” followed by “the sagacity to derive insight from the encounter” suggested by Andre et al. (2009), or the transformation of unexpected data into a new theory from Merton. McKay (2012) draws on the same Bergsonian distinction to frame her argument about the role of serendipity in artistic practice, where discovery and invention can be seen as ongoing and diverse. This draws our attention to the relationship between serendipity and creativity.

While there are many different definitions of creativity, novelty and utility are often understood to be essential criteria (for instance, see Newell et al. 1963 or Boden 1990). Rothenberg reviewed a collection of international perspectives on creativity and found “creativity involves thinking that is aimed at producing ideas or products that are relatively novel” (Rothenberg 1990, p. 2). And relatedly, Cropley (2006), following Austin (1978 & 2003), understands a creative individual as someone who “stumbles upon something novel and effective when not looking for it.” However, Cropley questions “whether it is a matter of luck,” because of the work and knowledge involved in the process forming an assessment of the finding. This again supports the notion of an inventive, creative aspect to serendipity.

We can also point to process-level parallels between definitions of serendipity and previous theories of creativity. Csikszentmihalyi’s perspective is particularly suggestive regarding the way in which an unanticipated, anomalous, and strategic datum, à la Merton, might arise and develop in social interactions:

“[C]reativity results from the interaction of a system composed of three elements: a culture that contains symbolic rules, a person who brings novelty into the symbolic domain, and a field of experts who recognize and validate the innovation.” (Csikszentmihalyi 1997, p. 6) [emphasis added]

In this case, novelty is attributed to “a person”: even so, it seems reasonable to assume that this person’s novel insights rely at least in part on the observation of data. This model can be compared with Csikszentmihalyi’s (1997, pp. 79–80, after Wallas 1926) five-stage model of the creative process, comprised of the steps preparation, incubation, insight, evaluation, and elaboration. This more elaborate model is a near match to the process-based model of serendipity from Lawley and Tompkins (2008), which takes the outward form of a sequence: prepared mind, unexpected event, recognise potential, seize the moment, amplify effects, and evaluate effects. However, Lawley and Tompkins’s model includes a feedback loop between “recognising potential” and “evaluating effects” that is not present in the Wallas/Csikszentmihalyi model. Moreover:

“[S]ometimes the process involves further potentially serendipitous events and sometimes it further prepares the mind (at which time learning can be] said to have taken place!” (Lawley and Tompkins 2008)
Serendipity is...

| chance encountering of information | sagacity to derive insight |
|-----------------------------------|---------------------------|
| unanticipated, anomalous, strategic datum |
| symbolic rules (that do not directly account for the data) | novelty | validation |
| preparation (including observations) | incubation | insight | evaluation | elaboration |
| prepared mind | unexpected event | recognise potential | seize the moment | amplify effects | evaluate effects |
| new connection | project value | exploit connection | valuable outcome | reflect on value |
| prepared | trigger | focus shift | bridge | result |

Table 1: Aligning ideas from several theories of serendipity and creativity. Lines 1-6 show increasing detail, moving from two to six phases; lines 7 and 8 bundle some of the steps together. Sources: (1) André et al; (2) Bergson; (3) Merton; (4) Csíkszentmihályi; (5) Wallas (as adapted by Csíkszentmihályi); (6) Lawley and Tompkins; (7) Makri and Blandford; (8) Section 3 of the current paper.

Makri and Blandford (2012a) propose a model that adapts Lawley and Tompkins, notably by combining the “prepared mind” and “unexpected event” into one first step, a new connection, which involves a “mix of unexpected circumstances and insight.” They also suggest that a parallel process of reflection into the “unexpectedness of circumstances that led to the connection and/or the role of insight in making the connection” is important for the subjective identification of serendipity. These authors also differ somewhat from Lawley and Tompkins in their interpretation of the nonlinear nature of the process. For Makri and Blandford, what is most important is that projections of value can be updated as the connection is exploited – for example, when it is discussed with others.

We distil our findings from the literature and draw parallels between them in Table 1 above. While the details differ, we can clearly see agreement that serendipitous discoveries can be dissected into different aspects, and the sorts of aspects that these might be. The several theories we have examined point to an idea of serendipity as creativity that happens in context, on the fly, with the active participation of a creative agent, but not entirely within that agent’s control. While the various theories we have examined differ from one another about just where “insight” takes place in the process – and some do not mention this term explicitly – none of them suggests anything to support a theory of “uninsightful” serendipity. We further explore the multi-faceted nature of serendipity below.
3 A computational model and evaluation framework for assessing the potential for serendipity in computational systems

We propose a model for serendipity in a computational context, which informs a working definition of the serendipity potential of a system. We follow this with a discussion of heuristics for applying the definition, and some examples.

3.1 Model and definition

Figure 1 integrates the concepts from the previous section into a computationally meaningful process model. The model is summarised in text form just below, in our working definition of the serendipity potential of a system.

![Diagram of the serendipity model](image)

A simplified process schematic, showing the key components of the model: the trigger (T), prepared mind (p, p'), focus shift (T'), bridge (B), and result (R); and the corresponding dimensions: chance (a), curiosity (b), sagacity (c), and value (d).

**Discovery:**
- **Generative process**
- **Feedback**

**Invention:**
- **Verification**
- **Evaluation process**

Fig. 1: Schematic representations of a potentially serendipitous process
Figure 1a focuses on the key features of “successful” serendipity. A potential trigger for serendipity, denoted here by $T$, has been perceived. The prepared mind corresponds to those preparations, labelled $p$ and $p'$, that are relevant to the discovery and invention phases, respectively, which may include training, current attitude, and access to relevant knowledge sources. A focus shift indicates that the trigger has now been discovered to be interesting. The newly-interesting trigger is denoted $T^*$, and is common to both the discovery and the invention phases. The bridge $B$ consists of the actions based on $p'$ that are taken on $T^*$ leading to the result $R$, which is then given a positive evaluation.

Fallibility is a “meta-criterion” for serendipity, and our definition of the serendipity potential of a system will revolve around examining the system’s main points of possible failure. As indicated in Figure 1a, (a) due to chance, the trigger may not arise or be observed; (b) due to insufficient curiosity, a trigger may not arouse the system’s interest; (c) due to insufficient sagacity, the system may not be able to transform a trigger that has captured its interest into a tangible result; and (d), a result may not be of any significant value.

Figure 1b expands this schematic into a sketch of the components of one possible idealised implementation of a serendipitous system. An existing generative process is assumed. In an implementation, this may be based on observations of the outside world, or it may be purely computational. In any case, its products are passed on to the next stage. After running this data through a feedback loop, certain aspects of the data are singled out, and marked up as “interesting.” Note that this designation does not necessarily arise all at once: in general it the outcome of a reflective process. In the architecture envisioned here, this process makes use of two primary functions: $p_1$, which notices particular aspects of the data, and $p_2$, which offers further reflections about those aspects. Together, these functions build up a “feedback object,” $T^*$, which consists of the original data and further metadata. This is passed on to an experimentation module, which has the task of validating this object’s purported interest, and determining what it may be useful for. This is again an iterative process. Once a result is generated, it is passed to a final evaluation module, and, from there, to further applications.

While feedback loops are present in several previous definitions of serendipity (and in Figure 1b), we will not explicitly include them in our definition of the serendipity potential of a system. Nevertheless, assuming that the system is updated (or updates itself) over time, there is nothing to prevent its serendipity potential changing over the course of repeated runs. Our model remains open-ended about the uses to which the valuable result may be put.

Along with these structural assertions, we propose several qualitative concepts that describe environments and architectures that can make serendipitous occurrences more likely. We suspect that serendipity will be more likely for agents who experience and participate in a dynamic world, who are active in multiple contexts, occupied with multiple tasks, and who avail themselves of multiple influences. These features are not included in the following definition of the serendipity potential of a system, but they may feature in more detailed descriptions of modules or operating environments.
Definition (The serendipity potential of a system). The evaluator should choose a lower threshold of value, $\epsilon$, and an upper threshold of likelihood, $\delta$, both in the interval $(0, 1)$. A family of comparison systems, $\mathcal{F}$, is selected. Then observations are made:

1. The systems process data that arises at least partially as the result of factors outside of their control. Amongst this data a trigger is observed by some proportion of the systems, $0 \leq a \leq 1$.
2. Assuming a trigger has been observed, some proportion of the systems, $0 \leq b \leq 1$, classify it as being especially interesting and subject it to further processing, constituting a focus shift.
3. Assuming that a trigger has been marked as interesting, some proportion of the systems, $0 \leq c \leq 1$, transform the trigger into a result.
4. This result is then rated by the evaluator as having a value, $d$, such that $\epsilon < d \leq 1$.

$\mathcal{F}$ should be expanded as long as this increases the size of the sub-population that ever becomes “successful” for each of the criteria (1)–(4). If the system we are interested in assessing belongs to this sub-population, and if $a \times b \times c < \delta$, then $1 - a \times b \times c$ is the system’s serendipity potential. (Otherwise, the system does not have serendipity potential.)

The primary challenge presented by a frequentist definition like the one above is that serendipity tends to be discussed with reference to one-off occurrences; thus, we consider the historical discovery of penicillin by Alexander Fleming or the historical invention of Velcro by George de Mestral, and so on. After the fact, we might be inclined to judge the probability of success at 100%, and beforehand, we might not even think to ask the question. This is where examples like the case history of Eugen Semmer are particularly useful.

Semmer (1843-1906) was a veterinary pathologist known for research into fowl cholera and anthrax (Saunders et al 1980), but perhaps better known for what failed to happen after he planned to conduct a post mortem analysis for two unwell horses. As it turned out, there was one crucial problem with his plan: “when he arrived in the morning he discovered that the animals had unexpectedly and inexplicably recovered” (Cropley and Cropley 2013, p. 75). Semmer determined that this was caused by the unintended presence of *penicillium notatum* spores in his laboratory. He proceeded to test this theory with further *in vivo* experiments on other animals.

“However, apparently blinded by the narrow nature of his special knowledge . . . he did not recognise that he had stumbled on an important life-saver (what we now call ‘antibiotics’), and instead went to considerable lengths to eradicate the spores from his laboratory.” (Cropley and Cropley 2013, p. 76)

In terms of our definition, we can understand the horses’ recovery to be a trigger, and Semmer’s further experiments to be a focus shift. In these respects his experience is comparable to that of Fleming’s famous encounter with bare
patches in his dirty petri dishes. However, Semmer’s failure to translate his experience into a valuable result allows us to bound $c$ from above, at 50% or less, for the “lab biology” systems shared by both Semmer and Fleming.

In a setting where a given computation system runs repeatedly, a population of separate runs can allow us to estimate scores on the relevant dimensions. Similarly, if the system involves multiple threads or agents, then frequentist modelling approach is a natural one to use.

This conception of serendipity potential allows us to specify a single number in place of the Likert-type data suggested by Makri and Blandford:

1. How unexpected were the circumstances that led to the connection being made? (Not at all/Somewhat/Very)
2. How insightful was the making of the connection itself? (Not at all/Somewhat/Very)
3. How valuable was or do you expect the outcome to be? (Not at all/Somewhat/Very)

(Makri and Blandford 2012b, p. 7) [emphasis modified]

Note, however, that the result’s value, $d$, does not factor into our definition of serendipity potential, except as part of a thresholding step that is used to determine whether serendipity potential is defined for a given system. This is because, in reflecting on prior descriptions of serendipity, it seems that what matters is the fact that the result is of value, rather than its absolute or overall value. In applying our definition, system designers and evaluators are asked to specify a threshold of value that they deem to be sufficiently significant.

3.2 Heuristics for applying the definition of serendipity potential

The constituent terms in the abstract model presented in Figure 1 are purposefully general. A trigger, for example, is not defined in terms of a specific data structure, nor is a bridge constrained to be drawn from a specific set of reasoning techniques. We view such generality as a strength, but it does leave further work for anyone who aims to apply this model. The definition of serendipity potential guides the user to focus on five key questions:

1. What is the comparison population?
2. What kind of data could constitute a “trigger”?
3. What causes a trigger to be designated as “interesting”?
4. What class of outcomes count as a “valuable result”?
5. How are results evaluated?

Although the process of answering these questions may be informed by heuristic concepts such as a “prepared mind,” “curiosity,” and “sagacity,” answers themselves should be given in computational terms. Such answers will be system-specific, but the following general guidelines provide a starting point.

Heuristic 1. Choose relevant populations to produce useful estimates. Our aim is to separate success from failure in a meaningful way at each critical point
in the process, and this can be done by figuring out what proportion of a relevant population is likely to meet the success criteria. We need not compute exact values for $a$, $b$, $c$, and $d$ if we can build informative estimates. Towards this end, we might choose to compare Alexander Fleming to lab biologists in general, or Charles Goodyear to other industrial chemists. In comparison to their peers, both were highly curious about and invested in the specific topics they were researching (Fleming 1964; Goodyear 1855). Their discoveries would accordingly be called “pseudoserendipitous” under Robert’s (1989) definition. One inference we can make here is that $b$ should be given a rather low rating for these researchers, since they knew what they were looking for, whereas only a relatively small proportion of biologists or chemists would recognise the corresponding trigger as a trigger (vide Semmer, for instance). Secondly, the pseudoserendipitous aspect of their work also means that, due to their perseverance and somewhat obsessive focus, Fleming and Goodyear had a higher than usual chance of encountering the trigger than members of the comparison population, and, so $a$, while still small, it was less small for these researchers than it would have been for their peers. As mentioned above, if the system has multiple threads or runs multiple times, this may present a natural comparison population. Note, however, that the comparison is only useful if the members of the population are sufficiently different. Our case studies in Section 4 will illustrate this point.

**Heuristic 2. Find the salient features of the trigger.** How can we estimate the chance of a trigger appearing, if every potential trigger is unique? Consider de Mestral’s famous encounter with burrs that precipitated the invention of Velcro™. There is a high chance of encountering burrs while out walking: many people have had that experience. We can estimate $a$ as high in this case. What is most remarkable about de Mestral’s experience is not that he encountered burrs – and certainly not that he encountered some particularly “special” burrs – but that he had the curiosity, resources, technical, and entrepreneurial mindset that caused him to think twice about the experience, and later, the sagacity (and tenacity) to transform his idea into a successful product using variations on then-current manufacturing techniques. More broadly, the question is not so much “what makes this data intrinsically different?” but rather, “how does the agent’s attention allow it to become extrinsically differentiated?” The trigger may in fact be a complex object or circumstance that develops over a period of time – in other words, it may be a pattern, rather than a unitary fact or “datum” that exists apart from interpretation. We generally understand patterns in terms of their constituent and contextual factors. Makri and Blandford’s (2012a) term “new connection” is apt because it suggests that the state of the “prepared mind” is important in establishing data as a trigger – although the concept of a “pattern identification” may be more widely applicable.

**Heuristic 3. Clarify the role of embedded evaluation.** “Embedded evaluation” is required at each of the major steps in our model: i.e., the system must form a preliminary assessment of the trigger in the process of perceiving it;
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centrally, it must re-evaluate the trigger to assign it some particular interest and effect a focus shift; it must make further relevant associations when forming the bridge; and typically, it will ascribe positive value to the final result. Identifying the locus of evaluative judgements can serve as a vital clue when applying the definition of serendipity potential, and especially when thinking through the focus shift. A focus shift happens when something that initially was uninteresting, neutral or even negative becomes interesting. According to our definition of the serendipity of a system, is not enough to simply subject the trigger to further processing: rather, it needs to be classified as being “especially interesting,” which implies framing it in a new context of evaluation. For example, a standard spell-checking program might suggest a substitution that the user evaluates as especially valuable, fortuitous, or humorous. However, we would not say that spell checking system has serendipity potential. Indeed, a standard spell checking program is, in itself, entirely predictable: assuming it is well-written, it provides more or less the same corrections that any competent speller would come up with. It does not discriminate between its inputs or generated results in an especially meaningful way.

Heuristic 4. Look at long-term behaviour to the extent that this is possible. Finally, many systems (including all of the examples that we consider in our case studies in Section 4) have an iterative aspect. This means that the outcome of one processing step may serve as a trigger for, or otherwise potentiate, subsequent discoveries. As Simon and Newell remarked, machines can improve their behaviour “not merely by memorizing specific patterns of successful behaviour, but by reprogramming themselves in ways that parallel at least some human learning procedures” (Simon and Newell 1958, p. 7). Keep in mind that if learning is taking place, further indeterminacy may need to be introduced or else the behaviour could become convergent, and potentially infallible, precluding rather than enhancing serendipity. It is worth emphasising this point: if we imagine a system that is infallible in every respect, it cannot be meaningfully compared to other systems. In this case we can just choose $F$ to be made up of the system itself and see that its likelihood of success is $1 > \delta$. For the same reason, any individual successful run taken on its own is not particularly informative; similarly, a long run of failures that does not take into account an eventual major success misses the point. Long-term behaviour of fallible systems may be hard to foresee, but to the extent possible, it should be included in estimates of a system’s serendipity potential.

Heuristic 5. Evaluate results in context. As described in Heuristic 3, it is crucial that the system makes its own evaluations. As per Makri and Blandford (2012a, p. 7), “forward facing projections are made on the potential value of the outcome” as the focus shift is effected, and again during the bridging phase. Even though we also expect the system to reflect on the value of the outcome (e.g., via an evaluation module as in Figure 1b), it is not strictly necessary for the system to have the last word. The definition of serendipity potential requires the evaluator to step in with an assessment of value. Judgements from
the user or another party can also confirm or deny the system’s evaluations. Third-party judgements of value may take into account additional features of context that are not directly available to either the system or its users.

3.3 A step-by-step example illustrating how the concept of serendipity potential can be applied to computational systems

To exemplify the concepts above before turning to more detailed case studies in Section 4, here we will consider variations on a theme from the tradition of “computational discovery in mathematics” (Colton 2007). Broadly speaking, even though fallibility is an overarching criterion, as richer and more robust system components come online, the potential for serendipity increases. We consider the following cases:

- **Zero potential for serendipity:** Automatic theorem proving
- **Low potential for serendipity:** Conjecture generation
- **Moderate potential for serendipity:** Conjecture and proof generation
- **High potential for serendipity:** Mining an online domain model

**System A. Zero potential for serendipity – Automatic theorem proving** A user of an automatic theorem proving system typically has in mind the theorem for which he or she wishes to establish a formal proof. That is, an informal proof already exists, and when translating this into a formal language, only minor logical and syntax errors stand in the way. These can be straightforwardly debugged. Once the proof has been fully specified, the theorem prover will return a certification. There seems to be no chance for serendipity here, at least not on the system side. Even if we were to construe an erroneous formal proof as a potential trigger for discovery, and a corresponding error message as a corresponding result, no focus shift has materialised, since the system does not assign special interest to any of its inputs. Furthermore, the binary result (valid/invalid) is not likely to be particularly significant to the user, who already expects to correct errors until the proof “goes through.” Thinking long-term, the hoped-for proof certification may be valuable, but we would not call it serendipitous.

**System B. Low potential for serendipity – Conjecture generation** Here we focus in on the part of the mathematical thought process that generates conjectures, without considering proof attempts. This was the historical course initially taken by the HR project with the NumbersWithNames program (Colton and Dennis 2002). Intuitively, NumbersWithNames can help with “the discovery part” of mathematics (Colton and Dennis 2002, p. 7). The trigger for this system was a given integer sequence, which may have been chosen at random or hand-selected by a user. The system was sometimes able to construct a bridge from the sequence to an interesting conjecture about the sequence (sans proof), which is considered to be a valuable, albeit preliminary, result. A case can be made for the system possessing a form of curiosity, which in
itself is non-exceptional, but which stands out in comparison to the population of system users, who would not be so painstaking. Namely, each potential trigger is submitted for further processing, via a range of transformation rules that explore outwards from the triggering sequence to discover potential statements that can be made about it. Only some of these are subjected to further processing, following a “pruning” step. Identifying the plausible conjectures among these requires some further common-sense ideas and straightforward numerical processing. Naturally, filtering the results list cannot guarantee that any of the generated plausible results will actually be of interest to the user. Here it is worth emphasising that, in practice, many of the interesting results from NumbersWithNames were found based on intelligent problem selection on the part of the system’s users, who were able to supply a preselected sequence of interest. Ultimately, the fact that NumbersWithNames could surface some interesting conjectures about these sequences suggests that it is sufficiently, if minimally, sagacious. Although its preparations are mathematically non-sophisticated, its various forms of rule-based processing meet the most basic conditions of an elementary prepared mind. NumbersWithNames can be contrasted with standard proof checking software in that, after the user provided a trigger in the form of an input sequence, NumbersWithNames carried out further processing to generate results that it could contextualise as unexpected, plausible, and therefore, potentially valuable. Work with the system produced surprising publishable mathematical results (Colton 1999).

System B’. Moderate potential for serendipity – Conjecture and proof generation
Here we consider embedding System B within a larger system that is able to assess generated conjectures using a plausibility measure, and, on this basis, to selectively construct proof-attempts. Later versions of HR took this route. Given a specific conjecture, System B’ can be discriminating in its curiosity and invest further processing selectively, whereas System B was not especially discriminating in its processing efforts. In other words, automated problem selection is a key advantage that System B’ obtains by using System B as a submodule. Assuming that proof attempts are successful reasonably often, System B’ will be convincing in its sagacity as well. Furthermore, its results will be strictly more informative than those of System B.

System C. High potential for serendipity – Mining an online domain model
In a more futuristic hypothetical example, we can imagine a system that has at its disposal a large database of formalised proofs, assorted mathematical concepts, and informal heuristics. Additionally, suppose that new data in a machine-accessible format is coming online all the time – perhaps the system deploys a next-generation parser on new papers as they are added to the mathematics Arxiv (cf. Ginev et al (2009)). Such a system could have a large collection of open problems that it is working on at any given moment, which, together with the aforementioned facts and heuristic patterns, constitute a considerably more robust prepared mind than in the previous systems. This system could take a highly discriminating approach to generating conjectures,
and apply a range of mathematical techniques to construct bridges from conjecture to proof. Each new paper or fragment of user interaction it encounters would constitute a potential trigger for discovery. Some of these contributions will have more generative potential than others. Importantly, the system would be able to judge for itself whether a given result is globally new. The fact that the system runs in an online manner means that chance plays a prominent role for this system. However, like the previous system, this one is fallible: for all its background knowledge, there is no guarantee that it will find any worthwhile results on any given day. Its “hit rate” will depend partly on the quality of the search strategies it uses. It would be straightforward to characterise the system’s search priorities using the dimension of curiosity. Again, the system could afford to be discriminating, with its allocation of attention driven by an interest in specific problems. The system’s heuristics for solving these problems would straightforwardly connect with the dimension of sagacity. One can go on to imagine a further layer of higher-order programs that would operationalise the search for new strategies and heuristics. The system is clearly situated in a dynamic world. It can avail itself of multiple influences by reading papers from different mathematical domains. Switching attention between proving new theorems and developing new search strategies and problem solving heuristics would give the system multiple tasks and multiple contexts for creativity.

4 Serendipity in computational systems: case studies

The three case studies considered here, respectively, apply our process model and definition of serendipity potential to evaluate an existing system, to design a new experiment, and to frame a grand challenge. The first two systems that we examine do not have serendipity potential according to our definition, although they are reasonable candidates that match many of our heuristic criteria. This helps to show that the definition is not overly inclusive. In each case study, we include qualitative remarks about future revisions that could increase the systems’ serendipity potential. As Campbell (2005) writes, “serendipity presupposes a smart mind”, and each of these examples suggest potential directions for further work in computational intelligence. Keeping in mind the heuristic ideas described in Section 3.2, these examples will only include estimated values for the dimensions $a$, $b$, $c$, and $d$ that serve to define serendipity potential. Throughout, we will assume the lower bound on value, $\epsilon$, to be low, and the upper bound on likelihood, $\delta$, to be moderate.

4.1 Case study: An existing evolutionary jazz improvisation system

4.1.1 System description

Jordanous (2010) reported on a system using genetic algorithms for computational jazz improvisation, which was later given the name GAmprovising (Jor-
danous 2012). Reevaluating GAmprovising can shed light on the manner in which evolutionary methods might be deployed to expand a computational system's serendipity potential.

GAmprovising uses genetic algorithms to evolve a population of Improvisors. Each Improvisor is able to randomly generate music based on various parameters such as the range of notes to be used, preferred notes, rhythmic implications around note lengths and other musical parameters (Jordanous 2010). After a cycle of evolution, each Improvisor is evaluated using a fitness function based on Ritchie's (2007) formal criteria for creativity. This model relies on user-supplied ratings of the novelty and appropriateness of the music produced by the Improvisor to calculate 18 metrics that are applied to judge the Improvisor’s creativity. The fittest Improvisors are used to seed a new generation of Improvisors through crossover and mutation operations.

### 4.1.2 Application of heuristic criteria

The GAmprovising system can be said to have a prepared mind in the form of its background knowledge of musical concepts and its ability to evolve Improvisors. At any given step, the system’s trigger for further improvisation is the combined outcome of previous mutations and the current user input. To be clear, at any given stage, a human evaluator is responsible for the system’s focus shift, since the user tells the system which improvisations are most valuable by selecting some of the generated examples and asking for more along those the same lines. Jordanous (2010) notes that this “introduces a fitness bottleneck.” In future versions of the system, autonomous evaluation could potentially take over for the human evaluator. For the purpose of this evaluation, we will consider the user as an “oracle” that is part of the system. Once the interesting samples have been collected (from whatever source), a bridge is then built to new results through the creation of new Improvisors. The results are the various musical improvisations produced by the fittest Improvisors (along with the parameters that have been considered fittest).

The population of all Improvisers across all generations in a given experiment comprise a relevant comparison population. As long as the user keeps providing input, the system will continue to evolve Improvisers. Accordingly, the chance of the user’s current preference informing each Improvisor in the new generation is “1.” Similarly, although the user may be highly selective in the previous round, the individual Improvisers are non-selective, so we rate curiosity as “1” as well. All of the Improvisers generate an at least minimally coherent result from this input, so sagacity should be rated as “1.” As for results, the system:

“[W]as able to produce jazz improvisations which slowly evolved from what was essentially random noise, to become more pleasing and sound more like jazz to the human evaluator’s ears” (Jordanous 2010).
4.1.3 Serendipity potential

Since the user is responsible for the system’s focus shift, strictly speaking Criterion (2) of our definition is not met, and the serendipity potential of the system itself is not defined. When we allow the user to play the role of an “oracle” for that step, the very reliability of the system bears against its overall potential for serendipity. Examining the population of Improvisers, the likelihood measure is $1 \times 1 \times 1$, with outcomes of moderate value at best. Accordingly, individual Improvisers do not have serendipity potential, since $1 > \delta$. This assessment may be seen to beg the question as to whether the system as a whole might have serendipity potential that emerges out of aggregate behaviour. Can we draw on the selective nature of the user’s preferences to rate curiosity as “low”? For example, what if we take the entire previous generation’s output as the trigger, and consider the proportion of Improvisers that survives to the next generation to be the “curious” contingent? That such a revision cannot on its own be sufficient can be seen by considering that, if it was, every evolutionary algorithm would have serendipity potential, which is clearly not the case. Indeed, evolutionary algorithms are best known for their reliably convergent behaviour. This leads to further doubts, in particular: is selective attention to one Improviser from the previous generation due to “especial interest,” or merely the routine selection of a maximiser? Reviewing Heuristic 3, we are reminded that “is not enough to simply subject the trigger to further processing,” and that what matters is framing the trigger “in a new context of evaluation.” The case for serendipity potential in the aggregate behaviour of the current version of GAmprovising does not seem particularly strong. However, these remarks begin to point in a fruitful direction: some further comments are given below.

4.1.4 Qualitative assessment

The GAmprovising system operates in a dynamic world, insofar as the user’s tastes and judgements may change over time. From the point of view of our definition of serendipity potential, the most obvious weak point of the system is that it isn’t able to “listen” to the music that it generates, which would allow it to much more fully exploit the dynamics of its own evolutionary process, and effect its own focus shift without consulting an outside oracle. Greater dynamism and, especially, more differentiation amongst the population of Improvisors could add the potential for serendipity to “GAmprovising 2”. More differentiation among Improvisers would mean that selective attention could (sometimes) be exceptional; e.g., a given hereditary line might become interested in a new style of play, much as in the real-world history of jazz music. A subsequent version of the system that could simultaneously cater to the tastes of multiple listeners would be occupied with a considerably more complex problem, spanning and integrating multiple contexts. The current version of the system uses one global fitness function; the system would be more convincing if the fitness function evolved to match the listener’s taste. Juggling
two or more fitness functions would give the future version of the system multiple tasks. Currently, multiple influences are present only in the design of the fitness function and settings for generative parameters, but, as above, these could be augmented with an evolving sense of musical taste.

4.2 Case study: Iterative design in automated programming

4.2.1 System description

Here we consider the design of a contemporary experiment with the FloWr flowcharting framework (Colton and Charnley 2014). FloWr is a tool for creating and running computational flowcharts, built of small modules called ProcessNodes. For the day-to-day user, FloWr offers a visual programming environment. However, it can also be invoked programmatically, on the Java Virtual Machine and via a new web API (Charnley et al 2016). The goals of the FloWr project are to create both a user-friendly tool for co-creativity and an autonomous Flowchart Writer. Our experiment targets the latter scenario, assembling available ProcessNodes into flowcharts automatically. This can be viewed as a simple example of automated programming.

In the backend, FloWr’s flowcharts are stored as scripts. These scripts list the involved nodes, together with their (input) parameters and (output) variable settings. Connections between nodes are established when one node’s input parameter references the output variable of another node. Inputs and outputs have type constraints. For instance, the WordSenseCategoriser node has a stringsToCategorise parameter, which needs to be seeded with an ArrayList of strings. However, the constraints also go beyond Java types: the output of WordSenseCategoriser is only useful when each of the entries in the input ArrayList can be parsed into a space-separated list of words. Another parameter, the node’s requiredSense, needs to be seeded with a string that represents one of the 57 British National Corpus Part of Speech tags. Given constraints of this nature, the first challenge in automated flowchart assembly is to match inputs to outputs correctly, and to make sure that all required inputs are satisfied. Pease et al (2013) envision this system being deployed in an online setting, with “a version of the software on a server, constantly generating, testing and evaluating the flowcharts it produces.”

4.2.2 Application of heuristic criteria

In the initial experimental design from Pease et al (2013), the system’s potential triggers are new information arising from various streaming services, the addition of new nodes, or the development of new flowcharts. The system’s prepared mind lies in a distributed knowledge base provided by the ProcessNodes, which provide metadata that describe constraints on their inputs and outputs, along with the global history of successful and unsuccessful combinations. Transforming a collection of nodes for which no known working
combination existed into a working flowchart is an occasion for a **focus shift**, in which the flowchart is evaluated. For example, the system might compare this flowchart with others that had been previously generated to discover patterns that could be exploited in the future. Successful combinations and any derived patterns would be stored, and referred to in future runs. The **bridge** to a new result is accordingly found by informed trial and error, building on previous outcomes. For Pease et al (2013), the intended **result** is simply a new valid combination of nodes that generates non-empty output. Reviewing this design in light of our model of serendipity and an initial round of prototyping, we made the observation that subsequent versions of the system might make use of more detailed evaluation functions, setting a higher bar for success. For example, Corneli et al (2015) described a potential future version of the system that would be tuned to search for flowcharts that generate poetry.

To apply the definition of serendipity potential, we must select a comparison population: in this case, we consider a population of agents that draw from the pool of available nodes and flowcharts, and attempt new constructions in a turn-based game. Most triggers (new flowcharts and new nodes) are available to the entire population. Specific output (e.g., from a streaming service) will only be available to a subpopulation. Even so, the globally available triggers can be expected to predominate, and the **chance** of encountering a given trigger can be rated as “*high*”. It is also likely that a given agent will focus its attention on each new trigger or (recalling Heuristic 2) patterned combination of triggers as they are encountered, so we also rate **curiosity** as “*high*.” Generating a successful result through combinatorial or heuristic methods does require a moderate degree of **sagacity**, but over time we expect most knowledge pertaining to flowchart construction to be available equally to all agents, so we rate this factor as “*high*.” Again, the criterion for attributing **value** is just that the combination of nodes generates non-empty output.

4.2.3 Serendipity potential

The associated likelihood score is **high × high × high**. This does not make a convincing case for the system having serendipity potential. Furthermore, until the system can produce results that a third party can judge to be valuable, it will not satisfy Criterion (4) from our definition. For now, we must conclude that with the set-up described above, the system does not have serendipity potential. This motivates a new set of experiments that meaningfully judge the value of generated flowcharts, generated texts, and explanatory heuristics, and that involve agents that are able to give specific, differentiated, attention to specific kinds of triggers. These changes would both result in and require increased curiosity and sagacity on the part of the system. Depending on the implementation strategy, the role of chance may shift as well.
4.2.4 Qualitative assessment

FloWr operates in a **dynamic world** in two senses: first, some of its input sources, like Twitter, are changing; also, the system’s available nodes and flowcharts change over time. Recording new flowcharts is the primary way in which the basic system design is dynamic. However, this preliminary design does not seem to deal with **multiple contexts**, **multiple tasks**, or to draw on **multiple influences**. In a future version of the system, goals might be specified in a more heuristic form, for example, by interpreting an input text in a given context. This would result in the strong possibility that some triggers present in the text or context would be missed, while others would be capitalised upon. Combining several strategies would meaningfully present the system with several tasks (e.g., if the aim was to generate poetry, one process might seek to flesh out a global structure, while another would fill in details of individual lines). Heuristics for evaluating output could bring domain-specific influences to bear.

4.3 Case study: A next-generation recommender system

4.3.1 System description

Recommender systems are one of the primary contexts in computing where serendipity is currently discussed. In the context of the current recommender system literature, ‘serendipity’ means suggesting items to a user that will be likely to introduce new ideas that are unexpected, but that are close to what the user is already interested in. These systems mostly focus on supporting **discovery** for the user – but some architectures also seem to take account of **invention** of new methods for making recommendations, e.g., by using Bayesian methods, as surveyed in Guo (2011). Current recommendation techniques that aim to stimulate serendipitous discovery associate less-popular items with high unexpectedness (Herlocker et al 2004; Lu et al 2012), and use clustering to discover latent structures in the search space, e.g., partitioning users into clusters of common interests, or clustering users and domain objects (Kamahara and Asakawa 2005; Onuma et al 2009; Zhang et al 2011). But even in the Bayesian case mentioned above, the system has limited autonomy. An argument for giving more autonomy to recommender systems so that they could invent new recommendation strategies can be made. This applies especially in complex and rapidly evolving domains where hand-tuning is cost-intensive or infeasible. Here, we emphasise a partial parallel between “serendipity as a service,” i.e., a serendipitous user experience that is induced by the recommender system, and system-internal serendipity triggered by the system-user interaction.

4.3.2 Application of heuristic criteria

With the above challenge in mind, we ask how serendipity could be achieved within a next-generation recommender system. In terms of our model, current
systems have at least the makings of a **prepared mind**, comprising both a user- and a domain model, both of which can be updated dynamically. User behaviour (e.g., following certain recommendations) or changes to the domain (e.g., adding a new product) could serve as a **trigger** that would cause the system to discover a new way to make recommendations in the future. This already happens in a limited sense with current systems, since, e.g., changes to average purchasing behaviour will change the specific recommendations that are made. In systems that are designed to induce serendipity for the user, the system can potentially bring about a focus shift for the user by presenting recommendations that are neither too close, nor too far away from what the user already knows. Here we consider what happens when the flow of information is the other way around. Note that it is unexpected pattern of behaviour in aggregate, rather than a one-off event, that is likely to provide grounds for the system’s **focus shift**. A **bridge** to a new kind of recommendation could be created by looking at exceptional patterns as they appear over time. For instance, new elements may have been introduced into the domain that do not cluster well, or a group of users may suddenly indicate a strong preference towards an item that does not fit their preference history. Clusters may appear in the user model that do not have obvious connections between them. A new recommendation strategy that addresses the organisation’s goals would be a valuable **result**.

We compare this hypothetical system with current recommender systems. All such systems have imperfect knowledge of user preferences and interests. The **chance** of a recommender system noticing some particular salient pattern in user behaviour seems quite “**low,**” at least at the moment. When a given pattern is noticed, adapting the recommendation strategy accordingly could be described as **curiosity**. It is important to note that these adaptations may work to the detriment of user satisfaction  – and business metrics  – over the short term. In principle, the system’s curiosity could be set as a parameter, depending on how much coherence is permitted to suffer for the sake of gaining new knowledge. However, most current systems are unlikely to be able to adapt significantly, even if new patterns are noticed. We rate this dimension as “**low-variable**.” Measures of **sagacity** would relate to the system’s ability to develop useful experiments and draw sensible inferences from user behaviour. For example, the system would have to select the best time to initiate an A/B test. A significant amount of programming would have to be invested in order to make this sort of judgement autonomously, and currently such systems are beyond rare, so we rate this dimension as “**low.**” The **value** of recommendation strategies can be measured in terms of traditional business metrics or other organisational objectives.

### 4.3.3 Serendipity potential

In this case, we compute a likelihood measure of **low × low-variable × low**, with outcomes of potentially high value, so that the envisioned system would have a relatively high serendipity potential. Realising such a system should be
understood as a computational grand challenge. Thinking long term (Heuristic 4) were such a system was ever realised, in order to maintain high value, continued adaptations would presumably be required.

4.3.4 Qualitative assessment

Recommender systems have to cope with a dynamic world of changing user preferences and a changing collection of items to recommend. A dynamic environment which nevertheless exhibits some degree of regularity represents a precondition for useful A/B testing. The system’s multiple contexts include the user model, the domain model, as well as an evolving model of its own programmatic organisation. A system matching the description here would have multiple tasks: making useful recommendations, generating new experiments to learn about users, and improving its models. In order to make effective decisions, a system would have to avail itself of multiple influences related to experimental design, psychology, and domain understanding. Pathways for user feedback that go beyond answers to the question “Was this recommendation helpful?” could be one way make the relevant expertise available.

4.4 Summary

While two of the three systems we examined failed to meet our criteria, all three show clear potential for serendipity pending further development. Here, we summarise these directions for future work.

1. A future version of the evolutionary music system would be more convincingly curious and sagacious if it could evaluate musical works without user intervention. It might also be able to tailor its fitness function to the individual user. Interaction between the system’s tasks and more dynamism in its influences would help differentiate individual threads or system runs. In a future version of the system, perhaps only some Improvisers would recognise and take interest in a given trigger (e.g., a specific musical pattern) and consequently only some would effect a focus shift. We would expect evolved results of more variable quality, as judged by the system – opening the exciting potential for it to learn identifiable musical skills.

2. The flowchart assembly process would need more stringent, and more meaningful, criteria for value before third-party observers would be likely to attribute serendipity to the system. In addition to raising challenges for autonomous evaluation (as in the evolutionary music system case), this requirement would impose more sophisticated constraints on processing in earlier steps. Embedding the system in a real-world context (e.g., responding meaningfully to user-submitted texts; cf. Corneli and Corneli (2016)) would require the system to be more sagacious and selectively curious.

3. The next-generation recommender systems we have envisioned needs to be able to make inferences from aggregate user behaviour. This points to long-term considerations that go beyond the unique serendipitous event.
Short-term value should be allowed to suffer as long as expected value over the long term is still higher. The symmetry between serendipity on the user side, and serendipity on the system side might be exploited: as a preliminary step towards building an artificially-intelligent recommender system, users might be assigned tasks that are designed to trigger serendipity on the system-side.

5 Discussion, future work, and conclusions

We began the paper with a pointer to a dilemma dating back to the origins of computational science. Our examples and case studies suggest that serendipity is not beyond the grasp of contemporary computing practice – even though systems with high potential for serendipity have arguably not been realised yet. Computer-supported serendipity or what we have called “serendipity as a service” has been well-studied. That work has been accompanied by collections heuristics for system users who may want to increase their own potential for serendipity (Makri et al 2014). However, previous scholarly and empirical attention to the potential for serendipity in computational systems has much more constrained.

For philosopher and media theorist Vilém Flusser, automation in a universe otherwise ruled by entropy is defined as follows:

“a self-governing computation of accidental events, excluding human intervention and stopping at a situation that human beings have determined to be informative.” (Flusser [1985] 2011, p. 19)

However, while these products are improbable “from the standpoint of the universe,” Flusser says, “from the receiver’s standpoint, they are still probable.”

In our definition of serendipity potential, we consider a localised context of evaluation in which new discoveries, and potentially even new patterns of discovery, are found or created. In order to affirm that a system has “serendipity potential,” our definition relies on the existence of an evaluator who deems these discoveries to be improbable. Some systems can be seen to have greater potential for serendipity than others: our case studies in Section 4 showed both positive and negative examples. The case studies also indicated ways to increase the potential for serendipity in the systems we examined.

According to Simon and Newell (1958, p. 6), “[i]ntuition, insight, and learning” have been close at hand in computing for some time now. And yet, practitioners in computational creativity (and creative computing) often focus on product evaluations rather than factors like these. Ritchie (2007) uses metrics that depend on properties that a reasonably sophisticated judge can ascribe to generated artefacts: “typicality”, i.e., the extent to which an artefact belongs to a certain genre, and “quality.” These are used as atomic measures from which more complex metrics, including “novelty,” can be derived. In recent years, artefact-centred evaluations are increasingly complemented by methods that consider process (Colton 2008) or a combination of product and process (Jordanous 2012; Colton et al 2014). Systems increasingly evaluate their own work
in light of an audience model or through other means, and may adapt their goals and behaviour accordingly. However, “accidents” arising outside of the control of the system (and ultimately, outside of the control of the researcher) might be deemed out of scope for computational creativity. Unexpected external effects could even be seen to invalidate research in this area.

We would argue that the concept of serendipity brings autonomous creative systems into clearer focus: not with an abstract notion of creativity *ex nihilo* or *ex se*, but creativity in interaction with the world. This requires a different mindset, and a different approach to system building and evaluation. Our model provides basic outlines that system designers and developers can use to increase the potential for serendipity in their systems. Each of the dimensions of our model – *chance*, *curiosity*, *sagacity*, and *value* – points to a range of challenges for future work on computational serendipity:

Russell et al (2015) advise researchers to consider verification, validity and security as well as control. An uncertain world requires autonomy to be added to the list, which means giving up some control, and accepting that there will be missed opportunities on the one hand, and that computers will devote resources to problems we would not have thought of on the other. As we considered ways to enhance the measure of serendipity potential in our case studies, we were led to consider computational agents that increasingly participate in “our world” rather than in a circumscribed and highly controlled microdomain. How can we give systems tools to not only face “more complex challenges” (Knight 2016) – but also to learn how to face entirely new ones? The four supportive factors for serendipity described in this paper – a dynamic world, multiple contexts, multiple tasks, and multiple influences – give some clues. Collectively, these factors strongly resemble our social reality, in which structure and meanings are emergent (Mead 1932). Whereas d’Inverno and Luck (2012) and Saunders (2002), among others, consider social agents in creative contexts, modelling the conditions of emergence presents a range of theoretical challenges (Loreto et al 2016). Colton et al (2015) outline a general programme for computational creativity, and examine perceptions of computational creativity among members of the public, computational creativity researchers, and existing creative communities. We should now add a fourth important “stakeholder” group in computational creativity research: computer systems themselves.

Our model offers systematic guidance on ways to encourage serendipity, and a new way to approach heuristics like “seizing opportunities” and “looking for patterns” from Makri et al (2014). Our case studies suggest specific ways to increase the serendipity potential in a range of computational systems. We hope the framework we have introduced will be useful for other efforts that aim to encourage serendipity in computational science and beyond.
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