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Building, evaluating and understanding socio-cultural AI: leveraging concepts and methods from human sciences

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Abstract

The recent evolution of artificial intelligence (AI) has led to its increasing integration into human culture. This growing presence of AI in human society raises important scientific questions - particularly those concerning the socio-cultural aspect of AI, which are crucial for better conceptualizing, evaluating, and designing future AI systems, as well as understanding their potential impact on the human society and culture. While this is a complex and nuanced topic, valuable insights can be drawn from psychology and human sciences, which have studied related aspects of socio-cultural behavior in humans and animals for decades. We explore three core scientific questions:

What does an intelligent system need to enter a human culture? Drawing on developmental psychological theories by Michael Tomasello and Jerome Bruner, we outlined core socio-cognitive abilities that we believe are most relevant for current AI research. We introduced The SocialAI School - a tool for generating environments designed to support evaluation and development of these abilities in artificial agents. We demonstrated various usages of the SocialAI School with RL and LLM-based agents. Our experiments revealed limitations of standard RL agents, particularly in their inability to generalize to new contexts, and showed that while LLMs exhibit behavior somewhat consistent with correctly inferring social cues, a performance gap still remains.

How can we characterize a culture encoded within an artificial system, such as a large language model (LLM)? We demonstrate that LLMs exhibit strong sensitivity to seemingly trivial context changes, which challenges the assumptions underlying many psychological questionnaires increasingly used to assess LLMs. We caution against naively using such questionnaires to draw general conclusions about LLM behavior. To investigate this, we systematically compare LLMs based their sensitivity to trivial context changes, i.e. on the stability of values expressed by simulated personas over various contexts induced by simulated conversations on different topics. We observe that some model families - Qwen, Mixtral, Mistral, GPT-3.5 - consistently exhibited higher stability in various experimental setups. Then, we construct a leaderboard by further extending this methodology. The latest results suggest that, while rank-order stability may be approaching its ceiling in this suite, a persistent gap in validation scores points to either remaining room for improvement or a fundamental limitation in applying human-centric theories to LLMs.

How does a human–AI culture change and evolve over time? Using the iterative chain design (a method adapted from the field of cultural evolution) we explored how different properties of human data influence the evolution of AI-generated content. We found that higher lexical diversity and greater gaussianity in human data were associated with increased deterioration over generations, while higher semantic diversity and overall data quality with smaller deterioration. We also observe that data properties from one domain had little influence on the data generated for another domain. These findings suggest that different parts of the internet may exhibit distinct evolutionary dynamics, shaped by the properties of the underlying human data.

The three questions discussed in this thesis are inherently complex and interdisciplinary. We presented only initial steps toward addressing them, leaving many open questions about the socio-cognitive capacities, internal representations, and cultural impact of AI systems. These questions are of utmost importance, especially as such systems are increasingly influencing human society and culture.

Keywords: artificial intelligence, deep learning, reinforcement learning, large language models, natural language processing, developmental psychology, social psychology, values, cultural evolution

Résumé

L'évolution récente de l'intelligence artificielle (IA) a conduit à son intégration croissante dans la culture humaine. Cette présence accrue soulève d'importantes questions scientifiques – notamment socio-culturelles – cruciales pour conceptualiser, concevoir et évaluer les systèmes d'IA, ainsi que comprendre leur impact potentiel sur la société. Bien que ce sujet soit complexe et nuancé, des éclairages précieux viennent de la psychologie et des sciences humaines, qui étudient depuis longtemps le comportement socio-culturel humain et animal. Nous explorons trois questions scientifiques centrales :

Quelles capacités un système intelligent doit-il posséder pour intégrer une culture humaine ? En nous appuyant sur les théories psychologiques du développement de Michael Tomasello et Jerome Bruner, nous avons identifié des compétences socio-cognitives fondamentales que nous jugeons particulièrement pertinentes pour la recherche actuelle en IA. Nous avons introduit The SocialAI School, un outil générant des environnements pour évaluer et développer ces capacités chez des agents. Nous avons démontré diverses utilisations de The SocialAI School avec des agents d'apprentissage par renforcement (RL) et des modèles de langage (LLM). Nos expériences ont mis en évidence les limites des agents RL classiques, notamment leur incapacité à généraliser à de nouveaux contextes. Nous avons aussi montré que, bien que les LLM manifestent des comportements partiellement compatibles avec l'inférence d'indices sociaux, un écart de performance subsiste.

Comment caractériser une culture encodée dans un système artificiel, tel qu'un modèle de langage de grande taille (LLM) ? Nous montrons que les LLM présentent une forte sensibilité à des changements de contexte apparemment triviaux, ce qui remet en question les hypothèses sous-jacentes à de nombreux questionnaires psychologiques de plus en plus utilisés pour les évaluer. Nous mettons en garde contre l'usage naïf de ces questionnaires pour tirer des conclusions générales sur le comportement des LLM. Pour cela, nous comparons systématiquement divers LLM selon la stabilité des valeurs exprimées par des personas simulés dans différents contextes. Nous observons que certaines familles de modèles – Qwen, Mixtral, Mistral, GPT-3.5 – manifestent une stabilité plus élevée dans différents dispositifs expérimentaux. Nous avons ensuite étendu la méthodologie pour construire un classement (leaderboard). Les résultats suggèrent que, bien que la stabilité relative semble plafonner, un écart persistant dans les scores de validation indique soit une marge d'amélioration, soit une limite des théories centrées sur l'humain appliquées aux LLM.

Comment une culture humain–IA évolue-t-elle dans le temps ? En utilisant le design en chaîne itérative (une méthode adaptée du domaine de l'évolution culturelle), nous avons exploré comment différentes propriétés des données humaines influencent l'évolution du contenu généré par l'IA. Nous avons constaté qu'une plus grande diversité lexicale et une distribution plus gaussienne des données humaines étaient associées à une détérioration plus marquée au fil des générations, tandis qu'une plus grande diversité sémantique et une meilleure qualité des données entraînaient une détérioration plus faible. Nous avons aussi constaté que les propriétés d'un domaine influencent peu les données générées dans un autre. Ces résultats suggèrent que différentes parties d'internet suivent peut-être des dynamiques évolutives distinctes, façonnées par les propriétés des données sous-jacentes.

Les trois questions abordées dans cette thèse sont fondamentalement complexes et interdisciplinaires. Nous n'en présentons ici que les premières étapes, laissant de nombreuses questions ouvertes concernant les capacités socio-cognitives, les représentations internes et l'impact culturel des systèmes d'IA. Ces questions sont cruciales, à mesure que ces systèmes influencent toujours davantage la société et la culture humaine.

Mots-clés: intelligence artificielle, apprentissage profond, apprentissage par renforcement, grands modèles de langage, traitement du langage naturel, psychologie du développement, psychologie sociale, valeurs, évolution culturelle

Introduction 1

The recent evolution of artificial intelligence (AI), particularly large language models (LLMs), has led to its increasing permeation into human culture. Humans now interact with AI systems in a variety of ways, ranging from classical chatbot assistants and educational tools to the generation and transformation of cultural artifacts such as social media content (Sadikoğlu et al. 2023), artistic works (Cetinic and She 2022), and even scientific papers (Buruk 2023). The growing presence of AI in human society and culture raises important scientific questions - particularly those concerning the socio-cultural aspect of AI, which are crucial for better conceptualizing, evaluating, and designing future AI systems. Moreover, understanding the potential impact of AI on the evolution of human society and culture is of paramount importance (Brinkmann et al. 2023; Tsvetkova et al. 2024). Here, we outline three core scientific questions that will be explored in this thesis. Those questions are very broad and complex, and in this thesis we address but a small fraction of the many aspects of these questions. The thesis is organized into three parts, each focusing on one of these questions by leveraging and adapting research and theories from psychology and related fields:

- How can we evaluate and build AI systems capable of *entering* an existing human culture, i.e. learning from, improving, and teaching a surrounding culture?
- How can we characterize and evaluate socio-cultural aspects of AI systems?
- How do cultures composed of AI agents (and humans) change and evolve over time?

The socio-cultural status of artificial systems is a complex and nuanced topic. However, we do not need to approach this topic from a blank slate. For decades, similar questions concerning the socio-cultural behavior of humans and animals have been explored in fields such as psychology (Miller 2002; Evans-Pritchard 2013), anthropology (Gilbert et al. 2025), ethology (De Waal 2016), and, more recently, cultural evolution (Mesoudi 2016). This body of research offers valuable insights that can guide our thinking, help us develop conceptual frameworks, formulate scientific questions, and even design appropriate experimental methodologies.

While psychology can offer valuable insights, it is crucial to proceed with caution, as the methods used to study those questions in humans cannot be directly applied to AI systems. There is a significant risk of overstepping: anthropomorphizing AI systems, confusing analogy with equivalence, or overlooking critical assumptions that may be violated when transferring psychological concepts to artificial systems. In fact, the crucial scientific questions regarding such transfers revolve precisely around how the analogies differ and what assumptions are broken. For example, when considering socio-cognitive abilities, it is important to recognize that even if AI systems and humans display superficially similar behaviors in certain contexts, the underlying mechanisms driving these behaviors are fundamentally different (Bender et al. 2021). Similarly, when adapting psychological questionnaires to study Large Language Models (LLMs), one must account for the fact that LLMs exhibit context-dependence to a far greater degree than is typically observed in humans (as we will show in Chapter 3). In order to do this, it is essential to rigorously study the limitations of transferring psychological concepts and methodology to AI. One of the key questions of this thesis is precisely how psychological and human science frameworks and methods can be *adequately* adapted for application to AI systems.

This thesis explores how theories, concepts, and methodology from social psychology and human sciences can be leveraged and adapted to formulate and explore scientific questions concerning the socio-cultural aspect of AI. It is organized into three parts, corresponding to the three scientific questions outlined above.

- **Part 1 (Entering a culture):** drawing on developmental theories, we outline and study the most basic concepts and abilities necessary for a system to enter an existing human culture (e.g. social inferences, role reversal). We present a tool, the SocialAI School, designed to facilitate generation of interactive social environments to foster research of those concepts.
- **Part 2 (Characterizing a culture):** following social psychology, we study the limitations of naively evaluating Large Language Models with psychological questionnaires. We explore how such psychological tools can be adapted for adequate application in AI. For instance, we adapt psychological methodologies to evaluate the expression and stability of basic personal values in LLM-simulated personas and populations across varying contexts.
- **Part 3 (An evolving culture):** following the research field of cultural evolution, we employ the iterative chain paradigm to investigate the factors influencing the evolution of AI-generated content in AI-human populations, such as on social media.

Before proceeding further, we would like to acknowledge that this thesis was written from the perspective of artificial intelligence, while engaging with a wide range of complex and nuanced subfields within psychology and cognitive science. Although we have made every effort to study these domains with care and rigor, it is possible that certain subtleties or perspectives were overlooked due to the breadth and diversity of the concepts explored.

1.1 What is "culture"?

Defining culture is inherently challenging due to the concept's elusive and multifaceted nature (Adilazuarda et al. 2024; Liu, Gurevych, and Korhonen 2024). Accordingly, different parts of this thesis adopt different working definitions and emphasize distinct aspects of culture.

Part I is primarily grounded in the work of Michael Tomasello, who described **human culture** as "the form of social organization that arose in the human lineage in response to specific adaptive challenges" (Tomasello 2019). Tomasello highlights two core dimensions of culture: the coordinative dimension—comprising conventions, norms, and institutions grounded in trust, commitment, and fairness—and the transformative dimension—wherein skills and knowledge are transmitted across generations through social learning, leading to what he calls the "ratchet effect" (cultural practices and products evolve and improve over time). He argues that the key distinction between human and non-human culture is that human culture exhibits **cumulative cultural evolution**, precisely due to this **ratchet effect**: "modifications and improvements stay in the population fairly readily (with relatively little loss or backward slippage) until further changes ratchet things up again" (Tennie, Call, and Tomasello 2009). Interestingly, he argues that while inventivness is common among other primates, it is the robust transmission of new discoveries that enables the ratchet effect and cumulative cultural evolution by preventing those discoveries from being forgotten. This perspective is the one we adopt in Part I.

Part II focuses on cultural expression in large language models. Recent research has adopted a variety of definitions and frameworks for understanding **culture** in the context of LLMs. For instance, Hershcovich et al. 2022 outline four dimensions along which cultures can vary: common ground, aboutness, objectives, and values. Pawar et al. 2024 draw from the definition proposed by White 1959, where culture is described as being: 1) within humans (e.g. concepts, beliefs, attitudes), 2) between humans (in social interactions), and 3) outside humans (e.g. pottery bowls, railroads, factories). Adilazuarda et al. 2024 take a somewhat broader approach proposing two types of "proxies of culture": demographic (e.g. ethnicity, religion) and semantic (e.g. names, emotions, food). Liu, Gurevych, and Korhonen 2024 present a taxonomy with three branches focusing on non-material aspects, linguistic variations, and social interactions. One approach to studying cultural expression in LLMs is to focus on one aspect of cultural expression - such as **values** - often assessed through psychological questionnaires like Geert Hofstede's VSM13 (Hofstede 2013) or instruments from the World Values Survey (Arora, Kaffee, and Augenstein 2023; Pawar et al. 2024). In Part II, we adopt this approach by primarily drawing on Schwartz's Theory of Basic Personal Values (Schwartz 1992a) and using the PVQ questionnaire (Schwartz 2021a) to evaluate value expression.

Part III is grounded in the field of cultural evolution, which adopts a broader definition of **culture** as "any socially (rather than genetically) transmitted information, such as beliefs, knowledge, skills or practices" (Mesoudi 2016). In this framework, evolution is characterized by three core principles: variation (entities vary in some characteristics), differential fitness (entities have different rates of survival and reproduction), and inheritance (parent and offspring correlate in those characteristics). We adopt those definitions in Part III.

1.2 Humans are a social species

The human species is profoundly and distinctively social. It has been argued that humans possess unique socio-cognitive abilities and motivations (Tomasello 1999). Moreover, human culture is characterized by *cumulative cultural evolution*, in which innovations and improvements are rapidly transmitted and preserved, enabling gradual and complex advancements in cultural artifacts—developments that would be unlikely to emerge through individual effort alone. This process underlies some of humanity's most extraordinary achievements, including scientific discovery, legal and ethical systems, and the capacity to sustain large, complex social groups (Tomasello 2019). Although at first it might seem that this sociocultural world is just another downstream product of cognition, decades of research in developmental psychology suggest the opposite (Vygotsky and Cole 1978; Bruner 1990; Tomasello 2019). Socio-cultural world, cultural knowledge, and socio-cognitive abilities and motivations are the foundation of both social and asocial intelligence, as well as of complex cultural evolution. The socio-cultural aspect of the human mind is a rich and intricate research domain. Unsurprisingly, a substantial body of work has been devoted to understanding the social and cultural dimensions of human intelligence.

Arguably the first scientist to emphasize the foundational role of the social environment in human intelligence was Lev Vygotsky. Vygotsky is credited with conceptualizing the Zone of Proximal Development (ZPD), which describes the gap between what a child can accomplish independently and what they can achieve with the assistance of a more knowledgeable other, such as a caretaker (Vygotsky and Cole 1978). He proposed that many social interactions are gradually transformed into cognitive processes through a process called *internalization*, which also enables higher-order cognitive abilities (Mirolli and Parisi 2011). For instance, when helping a child solve a difficult task, a caretaker might provide verbal guidance thereby breaking the task down into smaller, more manageable steps (social speech). Over time, the child may begin to guide themselves through similar problems by speaking aloud to themselves (private speech). Eventually, the child might utter such guidance in their head alone (inner speech). Throughout these processes, social and linguistic interactions are internalized and serve as key tools for further development (Morin 2012). Vygotsky's theories have had a lasting influence on cognitive science and developmental psychology (McLeod 2024). Another important thinker in this context is Ludwig Wittgenstein, particularly in his later work. He argued that meaning of a word is rooted in its *use* within a given context (Wittgenstein 1953). He illustrated this with examples such as the exclamation "Water!", which can take on vastly different meanings depending on the situation—e.g. a request, a warning, or a discovery. Wittgenstein likened the use of language and the inference of meaning to structured activities, which he called language games. His work is relevant for this thesis as it emphasizes that linguistic meaning is not fixed or abstract, but grounded in social interaction and pragmatic context.

The work of Vygotsky and Wittgenstein inspired many different directions of research into how humans, human culture, and environment interact and coevolve. Among these many lines of inquiry, this thesis focuses on those most relevant to addressing the scientific questions concerning the socio-cultural dimensions of AI introduced earlier. To this end, we outline three corresponding psychological research questions. The extensive bodies of work addressing each of these questions offer valuable insights that can inform our understanding of the previously introduced AI-related questions:

- What is required for a human to *enter* an existing human culture, i.e. to learn from, improve, and teach a surrounding culture?

- How can we characterize human culture and the socio-cultural aspect of humans ? How do different human cultures compare?
- How does human culture change and evolve?

It is important to note that these questions interact and that progress on one inevitably touches on the others. Nonetheless, for the sake of clarity and structure, we organize this thesis around the three bodies of research (each primarily addressing one question). These three research traditions form the foundation for the three parts of the thesis, where each part builds on one of them to study the corresponding AI-related question.

What is required for a human to *enter* an existing human culture, i.e. to learn from, improve, and teach a surrounding culture? Jerome Bruner's work has been at the forefront of the pragmatic tradition, emphasizing the central role of culture in human development (Bruner 1990). For instance, he presents a pragmatic account of how referencing, requesting and eventually linguistic communication develop through routinized social interactions (formats) in which those abilities are *necessary* to achieve various ends (Bruner 1985). He describes these interactions as scaffolded - the caretaker gradually helps less and demands more of the child to achieve those ends, thereby bootstrapping the child's development.

In contemporary developmental psychology, Michael Tomasello's Shared Intentionality Theory provides a detailed account of the uniquely human socio-cognitive abilities and motivations that, when combined with the relevant experience, underpin cumulative cultural evolution (Tomasello 2019). The theory proposes two key developmental stages. At around 9 months of age, the emergence of "joint intentionality" children begin to perceive a dyadic interaction as a joint agent striving towards the same shared goal. This enables various abilities such as using and understanding pointing gestures and role reversal, as well as motivations to bond through shared mental states, such as joint attention and joint goals. At around 3 years of age, the emergence of "collective intentionality" enables children to perceive collections of individuals as a joint agent. This enables children to view things from a normative perspective and consequently enables social norms and conventions. In Part 1, we explore the theories of Bruner and Tomasello in greater detail.

How can we characterize human culture and the socio-cultural aspect of humans ? How are various human cultures similar or different? In exploring these questions, we focus on value expression as one particular aspect of cultural expression. In social psychology, values are a central construct used to characterize cultural groups, societies, and individuals, as well as to explain motivations for attitudes and behavior (Schwartz 2012). A rich history of research in this field is reviewed in Kulich 2009 on which we greatly draw upon in this section. For instance, Kluckhohn and Strodtbeck's Value Orientations Theory (Kluckhohn and Strodtbeck 1961) constitutes one of the first dimensional and cross cultural theories of values. In Milton Rokeach's theory (Rokeach 1973), individuals' ranking of values were used to predict their behavior, preferences and beliefs. One of the most famous cultural values theory is that of Geert Hofstede, who identified five dimensions of cultural values by analyzing over 50 countries (Hofstede 2001). In contemporary research, two major projects further extended the study of cultural values: the GLOBE project*, which expanded Hofstede's framework to include six organizational values, and the World Values Survey (Haerpfer et al. 2020), which investigates global shifts in cultural values building on the work of Ronald Inglehart (Inglehart 2018).

Most relevant for this thesis is the work of Shalom Schwartz, who proposed models of values both at the individual and cultural level organized in a circular structure (for example, Power opposes Universalism, and both are orthogonal to Tradition) (Kulich 2009). In his individual-level theory, Schwartz outlined ten basic personal values (Schwartz 1992b). Those values and their structure remains consistent across different cultures, while their priorities differ between individuals and groups (Schwartz 2012). In Part II, we primarily build on this theory and the associated instruments.

How does human culture change and evolve? The field of cultural evolution views cultural change as an evolutionary process (Cultural Evolution Society 2025). In this framework, culture is defined as any socially transmitted information (Mesoudi 2016), and the evolution of cultural traits - such as texts, words, ideas - is characterized by three principles: variation, selection (different rates of survival and reproduction), and transmission (e.g. by social learning). While there are many different methods to study cultural evolution - ranging from computational and phylogenetic models to archaeological analysis - the transmission chain design is the most relevant for this thesis (Mesoudi 2023). In this design, information is given to a participant, who transfers it to a second participant, who in turn transfers it to a third participant, and so on. This method enables researchers to observe how small changes across successive transmissions can accumulate into larger cultural transformations that would be difficult to detect from individual-level changes alone. For instance, in Kirby, Cornish, and Smith 2008, iterative transmission of an artificial language led to an increase in its transmissibility by making it more learnable and structured. In Part 3, we build on this field and deploy a similar transmission chain design for LLMs.

1.3 The social aspect of AI

The socio-cultural aspect of AI has been thoroughly studied across various disciplines within AI research. Here, we discuss different settings in which the previously outlined scientific questions have been explored.

How can we evaluate and build AI systems capable of *entering* an existing human culture, i.e. learning from, improving, and teaching a surrounding culture? Creating an agent that interacts with humans or social peers has been studied from many different perspectives. Here, we outline but a non-exhaustive selection of prominent examples. Developmental robotics is an field that aims at designing artificial agents inspired by human development (Asada and Cangelosi 2022). Withing this field, the importance of social development and its interaction with

* https://globeproject.com/

other aspects of development has been clearly emphasized (Cangelosi et al. 2010). For example, Mirolli and Parisi 2011 advocated for a Vygotskyan approach to cognitive robotics, proposing that treating language as a cognitive tool could help the field address higher-level cognition. Interactions between humans and agents have also been studied with simulated environments, particularly in tasks such as embodied question answering (Gordon et al. 2018) and instruction following (Hill et al. 2020). Recently, goal-conditioned exploration processes have also been augmented with a social peer that helps an RL agent explore by using language as a cognitive tool (Colas et al. 2020). The social aspect of AI has also been extensively studied in multi-agent settings, where multiple agents are trained simultaneously. Notable examples include the design of training signals to foster cooperation (Jaques et al. 2019) or social learning (Bhoopchand et al. 2022), and demonstrating how a sophisticated curriculum supporting cooperation and tool use can emerge as a through of self-play (Baker et al. 2019).

Training of generative transformer-based models on massive amounts of internet data has taken the world by storm since the release of GPT-3 (Brown et al. 2020). The development of such models typically includes large-scale pretraining followed by fine-tuning, where models are further adapted and aligned for human use through techniques such as Reinforcement Learning from Human Feedback (Ouyang et al. 2022a) or Direct Policy Optimization (Rafailov et al. 2023). This process, can be viewed as first encoding vast aspects of human culture, and then refining the model through fine-tuning to make it more usable and aligned with human norms and expectations. In this sense, it can be seen as an attempt to enable LLMs to *enter* human culture. While one could not claim LLMs have *common sense* or social understanding alike that of humans, one could also not claim that progress has not been made in this direction. LLMs now perform surprisingly well on many of the conundrums only recently considered unsolvable, such as the Winograd schema problem (Kocijan et al. 2023). While such models still, and perhaps always will, make catastrophic blunders, they are often able to adequately integrate the sentence with the social context of the user's utterance, opening up countless applications. Let us consider a concrete example shown in Figure 1.1. The user requested an image of bookshelves with books and plants. We can see that the model correctly makes several assumptions, such as resolving that *them* refers to bookshelves and not books. We can also see it make a blunder: one plant appears to grow directly out of a book without being placed in a pot. The user then gives another instruction to "make it all black". This command is quite ambiguous without social context. For instance, it is not clear what *all* refers to, e.g. should the model return an image with all black pixels? This ambiguity can be resolved by interpreting the instruction within the social context: the user is using the model to generate an image of bookshelves, and it would not *make sense* for the user to suddenly request a completely black, featureless image. However, we must be cautious in interpretation. While the description above reflects how a human might infer the meaning of the instruction, there is no good reason to think the model made the same inference. Similarly, a human would likely infer from the first instruction that the plants should be placed inside pots since, in the real world, plants do not grow directly out of books. Nonetheless, the model appears to combine the user's utterances with the surrounding social context (in whatever way) to produce an adequate modification of the image, which makes it useful in this particular case.

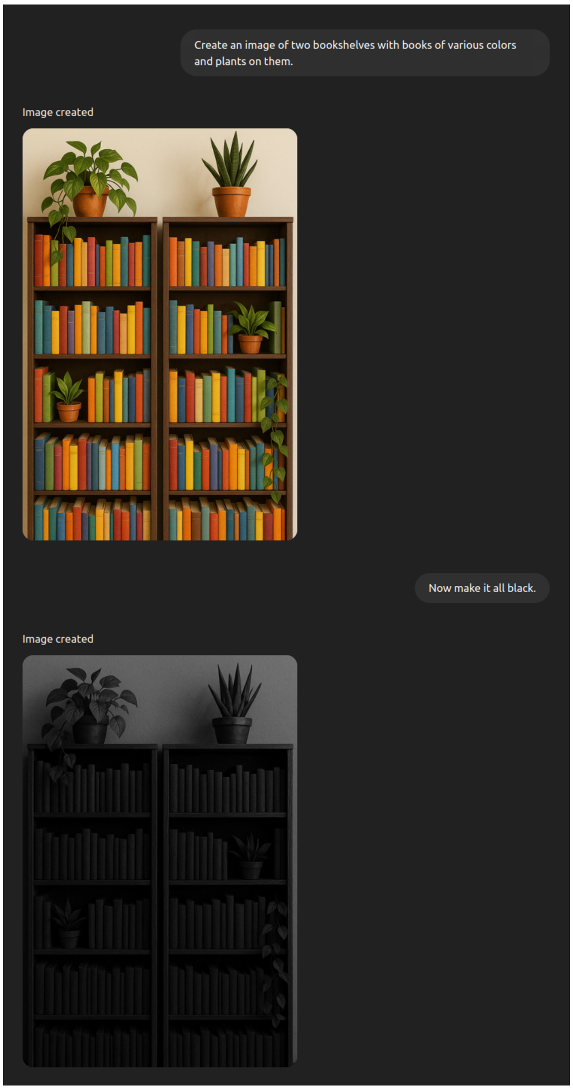


Figure 1.1: An example of GPT-4 correctly interpreting the instruction in the social context: “Now make it all black” darkens the image (as opposed to returning all black pixels). GPT-4 also makes a catastrophic blunder by drawing a plant growing out of a book. This suggests that, although the social inference was technically correct, it was likely not made through a human-like reasoning process.

Given these recent advances, it is not surprising that research aiming to test social competence of language models has been rapidly growing. Researchers have, for example, evaluated LLMs using linguistic adaptations of classical Theory of Mind tasks (Le, Boureau, and Nickel 2019; Sap et al. 2022), assessed their ability to interpret sentences within context (Ruis et al. 2022), and examined their performance on broader social commonsense reasoning benchmarks (Sap et al. 2019). In line with this thesis, this body of work also provides a cautionary tale about the risks of over-transferring psychological concepts and methodology to AI: following some research that over-claimed LLMs' Theory of Mind abilities (Kosinski 2023; Bubeck et al. 2023), subsequent work demonstrated that trivial alterations to those standard psychological tasks led to significant drops in model performance (Ullman 2023; Shapira et al. 2024). This was not lost on many researchers who had been critical of various grand claims - LLMs had been described as "stochastic parrots" (Bender et al. 2021) and suggested to operate in a new (different from human) mode of understanding (Mitchell and Krakauer 2023).

In Part I of this thesis, building on the developmental theories of Bruner and Tomasello, we outline a broader set of socio-cognitive abilities and concepts than those currently addressed in AI research. For instance, many AI research on the topic is either not grounded in psychology or is focused on testing Theory-of-Mind through Sally-Anne style experiments (Ma et al. 2023; Sarıtaş, Tezören, and Durmazkeser 2025). This, while being an interesting and relevant topic, captures a but narrow aspect of social-competence (Wang et al. 2025; Ma et al. 2023). Here, by building on extensive psychological theories we are able to outline a broader structure of relevant concepts and abilities. Furthermore, current benchmarks are mostly focused on static third-person evaluation (Ma et al. 2023; Wang et al. 2025). We introduce the *SocialAI School* a tool for procedural generation of interactive environments to foster research into these underexplored dimensions of social intelligence in interactive agents.

How can we characterize and evaluate socio-cultural aspects of AI systems? With the rapid advances in deep learning and generative AI, the question of how culture is encoded in such models has become increasingly pressing. It is well known that scientific research has historically overrepresented WEIRD (Western, Educated, Industrialized, Rich, and Democratic) cultures (Henrich, Heine, and Norenzayan 2010). Similarly, language models have been shown to exhibit a strong bias toward Western cultural norms (Atari et al. 2023; Johnson et al. 2022; Pawar et al. 2024). For instance, Western text is overrepresented in training corpora (Johnson et al. 2022), and evaluations have demonstrated that models' *default* behaviors are more aligned with Western values. Moreover, it has been shown that steering models toward other cultural perspectives is significantly more difficult (Atari et al. 2023; Adilazuarda et al. 2024; Tao et al. 2024). These biases are also evident in the models' inadequate responses regarding non-Western cultural contexts, such as suggesting drinking alcohol after an Islamic prayer (Naous et al. 2023). A naive approach to addressing these biases has been to simply include a greater diversity of languages in training datasets. However, this strategy remains insufficient, as many crucial aspects of culture (such as values or common ground) cannot be captured through language alone (Hershcovich et al. 2022). Recently, there has been a flourishing of research tackling these challenges, considering new approaches in training, usage strategies (e.g. cultural or sociodemographic prompting), and evaluation methodologies (Pawar et al. 2024).

Focusing on a particular aspect of cultural expression - value expression, part of the difficulty in encoding cultural diversity lies in balancing conflicting objectives of value pluralism and societal equity (Hershcovich et al. 2022). Different cultures possess different value systems, and care must be taken not to suppress cultural diversity by imposing a dominant cultural perspective. At the same time, some cultural norms may conflict with principles of equity and human rights, particularly when they marginalize or harm vulnerable groups. Johnson et al. 2022 propose that AI systems should align with a broad conception of human rights while still encoding multiple, potentially conflicting value systems. Ultimately, the appropriate balance between these objectives likely depends on the specific use case, as different applications may require different trade-offs.

In Part II of this thesis, we highlight the need for caution when using psychological questionnaires to study LLMs, particularly due to broken assumptions related to the severity of context dependence. We then adapt the methodology associated with Schwartz's Theory of Basic Personal Values to study the stability of value expression in LLM-simulated populations.

How do cultures composed of AI agents (and humans) change and evolve over time? A substantial body of research has explored the emergence of culture and communication. One of the earliest examples is the Talking Heads experiment (Steels 2015), in which a shared vocabulary emerged through interactions between embodied agents (installed at various locations around the world) as they played language games about the visual scenes in front of them. More recently, the role of environmental factors (e.g. resource availability, predators, climate) has been emphasized in the emergence of complex strategies like collaborative foraging (Nisioti, Litto, and Moulin-Frier 2021; Hamon, Nisioti, and Moulin-Frier 2023). Advances in deep learning have enabled these studies to scale to more realistic, high-dimensional environments (Lazaridou and Baroni 2020a; Moulin-Frier and Oudeyer 2020).

More directly related to this thesis, another line of research has studied the consequences of the increasing amount of AI-generated content entering human culture, particularly considering that this same content may be reused to train future models. This feedback loop has been shown to cause shifts in generated data distributions, leading to phenomena such as collapse (Shumailov et al. 2023) or bias amplification (Wang et al. 2024c). This effects have been studied both theoretically and empirically (Shumailov et al. 2023), including the image domain (Alemohammad et al. 2023a; Bertrand et al. 2023a) and the language domain (Dohmatob et al. 2024; Gerstgrasser et al. 2024a).

In Part III of this thesis, we expand on this line of work by investigating how different human data properties influence the dynamics and intensity of such distributional shifts over time.

1.4 Summary and Contributions

This section provides a brief overview of the three parts of this thesis. Each part addresses the overall question of how psychology and the human sciences can inform and support AI, by focusing on one of the scientific questions outlined in the opening section of this chapter. Each part concludes with a "From psychology" section, where we discuss how concepts and methodology were borrowed and adapted for AI.

As humans, we seem to effortlessly engage in coordinated social interaction with others. Throughout our development we quickly identify relevant facets of the social environment to efficiently enter a surrounding culture, i.e. learn from, improve, and finally teach our culture to future generations. In Part I (Chapter 2), we follow the developmental theories of Jerome Bruner and Michael Tomasello, which we discuss in detail, and then outline some of the most basic concepts and abilities relevant for a system to enter an existing human culture. More precisely, following the developmental theory of Michael Tomasello, we focus on three aspects of sociality, and from each we outline concepts we deem most relevant for AI at the moment: 1) regarding social cognition: the ability to infer what others see and to engage in joint attention, 2) regarding communication: the development of referential communication through pointing and the beginnings of conventionalized communication through simple language, and 3) regarding cultural learning: imitation and role reversal imitation. In addition, we outline two concepts from Jerome Bruner's theory: formats and scaffolding. Then, we present a tool - The SocialAI School, which facilitates the generation of procedural environments covering the outlined concepts and abilities. The environments can be used with classical multi-modal RL agents, but they can also be instantiated in pure text to study LLMs. We then present a series of case studies using SocialAI to study the outlined concepts and abilities with RL agents as well as with LLMs. Our experiments demonstrate the diversity of studies that can be conducted with the SocialAI school, highlight the limitations of standard RL agents, and show that while large language models exhibit behavior to an extent consistent with correctly inferring social cues, a performance gap remains - one whose size appears to depend on the problem at hand.

One way to evaluate and characterize human value expression has been through the use of psychological questionnaires. In Part II, we study the limitations of using psychological questionnaires with LLMs. Then, we adapt psychological methodology to evaluate the expression and stability of basic personal values in LLM-simulated personas and populations over different contexts. First, in Chapter 3 we present a positioning where LLM are seen as superpositions of perspectives - rather than exhibiting *a* persona, *a* culture, or *a* set of values, LLMs' behavior is always conditioned on the context (perspective). That is to say, providing a context (e.g. a Wikipedia article) collapses the superposition of perspectives into a single perspective (e.g. the perspective of the writer of the article). We show that asking the same questions through different textual formats leads to drastic changes in the answers. Then, in Chapter 4, we leverage the methodology used to study the stability of human values to study the stability of LLM-simulated personas and populations and provide an set of experiments where we compare LLMs based on their robustness to context changes when simulating populations. We observed consistent trends, with the Mixtral, Mistral, GPT-3.5, and Qwen model families appearing more stable. These trends are also confirmed on downstream behavioral tasks. LLMs studied in those experiments exhibited much lower than human stability (despite the comparison being skewed in the humans favor), which further diminished over longer conversations. This insight highlights the limitation of the studied LLMs and motivates future research on models specialized in simulating coherent populations of individuals. We further adapt this methodology to create a leaderboard where new LLMs are constantly evaluated and compared in real time. On the leaderboard we observed the benefit of using CoT prompting, and, more generally, the latest leaderboard results suggest that while value stability may be approaching its ceiling, the persistent gap in CFA validation scores points to either remaining room for improving value expression in LLMs or a fundamental limitation in applying human-centric theories, such as Schwartz's, to these models.

With the increasing influx of AI into human culture many questions regarding the dynamics of human-AI cultural evolution emerge. In Part III (Chapter 5), we study the evolution of generated social media content over iterative transmissions. We fine-tune LLMs on social media posts written by humans and by previous generations of LLMs, and study the evolution of the generated content. We found that higher lexical diversity and greater gaussianity in human data were associated with increased deterioration over generations, while higher semantic diversity and overall data quality with smaller deterioration. We also observe that data properties from one domain had little influence on the data generated for another domain. These results suggest that different parts of the internet may exhibit distinct evolutionary dynamics, driven by variations in their underlying data properties.

1.5 Publications

Journals:

- **Grgur Kovač**, Adrien Laversanne-Finot, and Pierre-Yves Oudeyer (2022). 'Grimgep: learning progress for robust goal sampling in visual deep reinforcement learning'. In: *IEEE Transactions on Cognitive and Developmental Systems* 15.3
- **Grgur Kovač**, Rémy Portelas, Peter Ford Dominey, and Pierre-Yves Oudeyer (2024). 'The SocialAI school: a framework leveraging developmental psychology toward artificial socio-cultural agents'. In: *Frontiers in Neurorobotics* Volume 18 - 2024
- **Grgur Kovač**, Rémy Portelas, Masataka Sawayama, Peter Ford Dominey, and Pierre-Yves Oudeyer (Aug. 2024a). 'Stick to your role! Stability of personal values expressed in large language models'. In: *PLOS ONE* 19.8

Conferences:

- **Grgur Kovač***, Jérémy Perez*, Rémy Portelas, Peter Ford Dominey, and Pierre-Yves Oudeyer (2025). 'Recursive Training Loops in LLMs: How training data properties modulate distribution shift in generated data?' In: *Proceedings of EMNLP 2025 (Oral).*
- **Grgur Kovač**, Rémy Portelas, Masataka Sawayama, Peter Ford Dominey, and Pierre-Yves Oudeyer (2024b). 'Stick to your Role! Stability of Personal Values Expressed in Large Language Models'. In: *Proceedings of the Annual Meeting of the Cognitive Science Society*. Vol. 46
- Jérémy Perez, **Grgur Kovač**, Corentin Léger, Cédric Colas, Gaia Molinaro, Maxime Derex, Pierre-Yves Oudeyer, and Clément Moulin-Frier (2025). 'When LLMs Play the Telephone Game: Cultural Attractors as Conceptual Tools to Evaluate LLMs in Multi-turn Settings'. In: *The Thirteenth International Conference on Learning Representations*

Preprints:

- **Grgur Kovač**, Masataka Sawayama, Rémy Portelas, Cédric Colas, Peter Ford Dominey, and Pierre-Yves Oudeyer (2023). 'Large language models as superpositions of cultural perspectives'. In: *arXiv preprint arXiv:2307.07870*

Workshops:

- **Grgur Kovač**[*], Rémy Portelas[*], Katja Hofmann, and Pierre-Yves Oudeyer (June 2021). 'SocialAI 0.1: Towards a Benchmark to Stimulate Research on Socio-Cognitive Abilities in Deep Reinforcement Learning Agents'. In: *NAACL*. Accepted at NAACL ViGIL Workshop 2021. Mexico City, Mexico (*Spotlight*)
- **Grgur Kovač**, Rémy Portelas, Peter Ford Dominey, and Pierre-Yves Oudeyer (July 2023). 'The SocialAI School: Insights from Developmental Psychology Towards Artificial Socio-Cultural Agents'. In: *TOM 2023 -First Workshop on Theory of Mind in Communicating Agents - ICML 2023 Workshop*. Honolulu (Hawaii), United States
- Guillaume Pourcel, Thomas Carta, **Grgur Kovač**, and Pierre-Yves Oudeyer (2024). 'Autotelic LLM-based exploration for goal-conditioned RL'. In: *Intrinsically Motivated Open-ended Learning Workshop at NeurIPS 2024*

Tools:

- Leaderboard: **Grgur Kovač**, Jérémy Perez, Rémy Portelas, Masataka Sawayama, Peter Ford Dominey, and Pierre-Yves Oudeyer (July 2024). *StickToYourRoleLeaderboard* [†]
- LLM4Humanities (a toolkit for qualitative data analysis using LLMs) [‡]

[*]Shared 1st authorship.

[†] https://huggingface.co/spaces/flowers-team/StickToYourRoleLeaderboard
[‡] https://github.com/flowersteam/LLM4Humanities

Part I

Entering a culture

2 The SocialAI School

What is this chapter about? This chapter focuses on the question "How can we evaluate and build AI systems capable of *entering* an existing human culture, i.e. learning from, improving, and teaching a surrounding culture?". AI research on socially interactive agents has largely focused on evaluating socio-cognitive abilities in complex models—such as large language models (LLMs)—or on studying the emergence of culture in multi-agent systems. Here, we argue that AI should also investigate the socio-cognitive abilities required for *entering* an existing culture, and that such research should be informed by insights from developmental psychology. To this end, we draw on the theories of Michael Tomasello and Jerome Bruner, introducing key concepts and socio-cognitive abilities that we believe to be important for current AI research. Those concepts include social cognition (e.g. joint attention, perspective taking), communication, cultural learning, formats, and scaffolding. We present The SocialAI school - a tool including a customizable parameterized suite of procedurally generated environments, designed to facilitate research on these topics. We demonstrate its by exploring the outlined concepts through experiments with both reinforcement learning (RL) agents and LLM-based agents. Our results show that while standard RL agents can learn to solve tasks when trained directly on them, they struggle to generalize to new contexts. Experiments with LLMs suggest that, although these models exhibit behavior partially consistent with interpreting social cues, a performance gap remains—and the size of this gap appears to be task-dependent. The main aim of this work is to engage the AI community around the problem of social intelligence informed by developmental psychology and to provide a tool to simplify first steps in this direction. Future work could explore a wide range of experiments, both using the current SocialAI environments and by extending them to support more complex scenarios.

Timeline and Contribution: The first part of the project (not discussed here) was done in 2021 in shared first authorship with Rémy Portelas. Then the project changed directions to be strongly grounded in developmental psychology an the theories of Michael Tomasello and Jerome Bruner. The second part of the project (discussed in this chapter) was done in 2022 in sole first authorship.

Scientific output:

- Journal: **Grgur Kovač**, Rémy Portelas, Peter Ford Dominey, and Pierre-Yves Oudeyer (2024). 'The SocialAI school: a framework leveraging developmental psychology toward artificial socio-cultural agents'. In: *Frontiers in Neurorobotics* Volume 18 - 2024
- Workshop: **Grgur Kovač***, Rémy Portelas*, Katja Hofmann, and Pierre-Yves Oudeyer (June 2021). 'SocialAI 0.1: Towards a Benchmark to Stimulate Research on Socio-Cognitive Abilities in Deep Reinforcement Learning Agents'. In: *NAACL*. Accepted at NAACL ViGIL Workshop 2021. Mexico CIty, Mexico (*Spotlight*):

- Workshop: **Grgur Kovač**, Rémy Portelas, Peter Ford Dominey, and Pierre-Yves Oudeyer (July 2023). 'The SocialAI School: Insights from Developmental Psychology Towards Artificial Socio-Cultural Agents'. In: *TOM 2023 -First Workshop on Theory of Mind in Communicating Agents - ICML 2023 Workshop*. Honolulu (Hawaii), United States

*Shared 1st authorship.

2.1 Motivation

Given the central role that social cognition plays in human intelligence and cultural evolution, it is natural that AI research aspires to model aspects of our social competence. To think creatively, generate original solutions, or identify novel and meaningful problems, a system would need to learn our values, but also learn how we see and understand the world. Such a socially competent system could potentially participate in our cumulative cultural evolution - improving our concepts, theories, inventions, and even creating new ones, i.e. **enter human culture**.

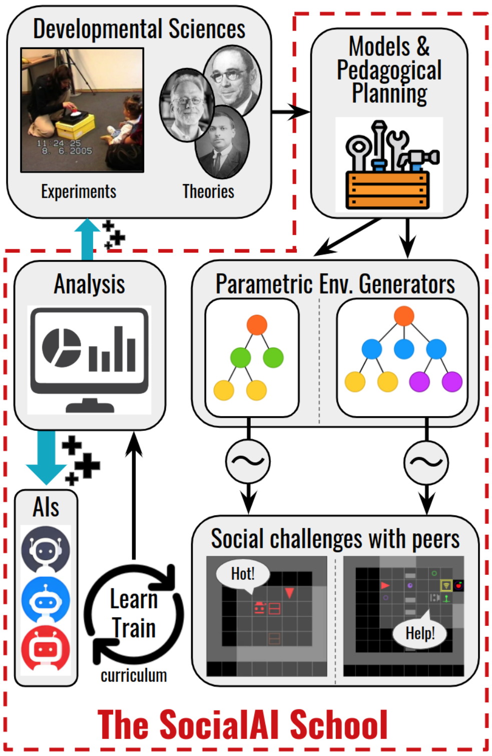


Figure 2.1: The SocialAI School provides technical and conceptual tools aiming to simplify research seeking to design socially proficient artificial agents.

Enriching AI with those skills also has numerous practical implications. Socially competent robots, capable of social learning, would be much easier to deploy and adapt to novel tasks and tools. For example, performing collaborative tasks with a robotic learner able to detect, learn and reuse context-dependent sets of communicative gestures/utterances could be easily integrated into human teams, without requiring humans to adopt new conventions. Furthermore, robots capable of learning human values and moral norms will be capable of performing tasks in the constraints defined by those values.

AI research on interactive agents has traditionally focused on tasks such as navigation and object manipulation, often stripped of any social dimension (Mnih et al. 2015; Lillicrap et al. 2016). When sociality is studied, it is typically within multi-agent settings, where the primary emphasis lies on the *emergence* of complex behavior (Jaques et al. 2019), frequently with only limited grounding in developmental psychology (Baker et al. 2019). While these research directions are both valuable and important, the focus of this work is different: we concentrate on the challenge of *entering* an already existing, complex human culture. And we argue that it can be beneficial to be informed by developmental psychology theories. We argue that drawing on theories from developmental psychology can provide useful guidance in addressing this challenge.

In the rapidly growing field of large language models, research on social cognition has often taken the form of proof-of-concept simulations (Park et al. 2023), or systematic benchmarks focusing on general social reasoning (Sap et al. 2019; Ruis et al. 2022; Zhou et al. 2023) or Theory-of-Mind (Le, Boureau, and Nickel 2019; Gandhi et al. 2023). The majority of evaluation on the social competence of LLM remains either not heavily grounded in psychology or focuses on false-belief queries (representing a narrower subset of social-intelligence in general (Ma et al. 2023)). Similarly, the majority of such evaluations remains in the form of static third person queries (Ma et al. 2023; Riemer et al. 2024).

Here, we propose to make a step in filling those gaps by outlining concept and abilities strongly grounded in developmental psychology theories of Michael Tomasello and Jerome Bruner, and by focusing on RL and LLM-based agents in interactive social environments. Crucially, this chapter does not claim to offer a complete solution for constructing a socially competent agent—a goal that is both far-reaching and deeply complex. Rather, we argue that grounding AI research in the concepts discussed in this chapter is a promising step forward. We argue that concepts from developmental psychology can serve as signposts for AI research, offering directions and insight in defining short term goals. Given that the outlined skills are at the very core of human social and cognitive competences, artificial agents aimed at participating in and learning from social interactions with humans are likely to require the same core competences. To support this effort, we introduce the *SocialAI School* - a tool designed to help researchers begin to systematically explore and evaluate these core socio-cognitive capacities in interactive artificial agents.

Following the theories of Michael Tomasello and Jerome Bruner, this work identifies a richer set of socio-cognitive skills than those currently considered in most of the AI research. In Tomasello 2019, the theory is presented in eight facets. We focus on three of these and, from each, outline the specific concepts and abilities we consider most relevant for current AI.

1. social cognition: the ability to infer what others see and to engage in joint attention
2. communication: the development of referential communication through pointing and the beginnings of conventionalized communication through language

3. cultural learning: the use of imitation and role reversal imitation in social learning

We also outline two concepts from Jerome Bruner's work:

1. formats: they refer to the way in which social interactions are structured and presented
2. scaffolding: it refers to the temporary support provided by a caretaker to help a learner achieve a task that would be otherwise too difficult.

Together, these concepts form the conceptual foundation for the framework presented in this chapter.

Based on this set of target abilities, we construct the SocialAI school, a tool (based on MiniGrid (Chevalier-Boisvert, Willems, and Pal 2018)) which enables the construction of social grid-world environments. These environments are designed to be both rich and tractable, allowing for systematic investigation into the acquisition of social competence in artificial agents. The social environments are organized according to the key cognitive science experiments used to study the social development in children.

In our experiments, we aim to show the versatility of the experiments which could be conducted with the SocialAI school. In the max text, we present experiments regarding the following questions: generalization of social inferences (the pointing gesture) to new contexts, recreating an experiment from cognitive science (to study the knowledge transfer during role reversal), and the impact of a scaffolded environment on the agent's learning. To show the diversity of agents which can be used, we conduct those experiments with RL agents, and present an additional case study with LLMs as interactive agents. In the Appendix, we explore the remaining concepts such as linguistic inferences, joint attention, and imitation. We hope this work encourages future research that expands on these initial studies—by introducing new socio-cultural scenarios, exploring different architectures or training regimes, and further probing the mechanisms underlying social competence in AI systems.

We outline the following main contributions of this work:

- An introduction to Michael Tomasello's and Jerome Bruner's theories on child development and core socio-cognitive abilities
- An outline of a set of core socio-cognitive abilities important for current AI research
- The SocialAI school: a tool including a customizable procedural generation suite of environments aiming to simplify studies of socio-cognitive abilities of AI agents
- Examples of case studies demonstrating how SocialAI can be used to study the outlined concepts and questions regarding socio-cognitive abilities in AI

Social agents are not objects Although social peers could be seen as merely complex interactive objects, we argue they are fundamentally different in nature. Social agents (e.g. humans) posses rich and dynamic internal states such as intentions, moods, knowledge states, preferences, emotions, and so on. In cognitive science, an affordance refers to what things or events in the environment afford to an organism (Gibson 1977). The resulting set of possible interactions with peers (social affordances Carvalho 2020) is essentially different from those with objects (classical affordances). A flat surface can afford "walking-on" to an agent, while a peer can afford "getting help from". The latter is a social affordance, which may require a social system and conventions (e.g. politeness), implying that social peers have complex internal states and the ability to reciprocate. Successful interaction might also be conditioned on the peer's mood, requiring communication adjustments. Training an agent for such social interactions most likely requires drastically different methods – e.g. different architectural biases – than classical object-manipulation training. In this chapter, we simulate such social interactions using scripted peers. We argue that studying isolated social scenarios featuring scripted peers in tractable environments is a promising first step towards designing proficient social agents.

2.2 Related Work

Earlier calls for socially proficient agents This paragraph aims to connect this thesis with earlier efforts in developmental robotics (Asada et al. 2009; Cangelosi and Schlesinger 2014), which studied how to leverage knowledge from the cognitive development of human babies into embodied robots. Within this field, multiple calls for developing the social intelligence of autonomous agents have already been formulated (Billard and Dautenhahn 1999; Lindblom and Ziemke 2003; Mirolli and Parisi 2011). We aim to further motivate the relevance of such concepts towards further progress in deep reinforcement learning (DRL) and AI.

Human-Robot Interaction Human-Robot Interaction (HRI) provides a well-established body of work focused on interactions with knowledgeable human teachers. In this context, researchers have explored how to provide interactive teaching signals to their agents through instructions (Grizou et al. 2014), demonstrations (Argall et al. 2009; Grollman and Billard 2011), corrective advice (Celemin and Solar 2015), and even narratives (Mealier et al. 2017). A review of this field Vollmer et al. 2016 discusses pragmatic frames (formats) and notes that restricted predefined (not learned) interaction protocols are usually used, and suggests the study of a broader set of social situations. This is especially timely now that RL and DRL are increasingly being deployed in real-world humanoid social robots (Qureshi et al. 2018; Akalin and Loutfi 2021).

Disembodied Social Interaction Understanding Another line of work has focused on disembodied machine learning models trained to interpret synthetic images or videos of social interactions. This literature typically adopts one of two experimental paradigms: classification and prediction. In classification settings, the objective is to correctly label the nature of an observed social scenario, e.g. is the interaction surprising or expected (Shu et al. 2021), are agents being cooperative, neutral or adversarial (Shu et al. 2020). Other works considered more precise scenario classifications (Netanyahu et al. 2021; Tejwani et al. 2021). For instance, in two-agents scenarios, Netanyahu et al. 2021 proposed a Bayesian approach to jointly detect each agent's goals (protect object, move object) and their relative relationships (friends, opponents). In prediction tasks, machine learning models have been evaluated on their ability to predict agents' actions in Theory of Mind experiments (Rabinowitz et al. 2018; Baker, Saxe, and Tenenbaum 2011), as well as in more general social perception assessments (Netanyahu et al. 2021).

While our ambition aligns with the aforementioned works - namely, encouraging machine learning researchers to study social interactions - this work advocates for an embodied and interactive perspective on sociality.

Large Language Models Various work evaluated LLMs on textual social reasoning tasks (Ma et al. 2023; Ye et al. 2025b). Sap et al. 2022 showed that such models struggle on two benchmarks: SocialIQA (Sap et al. 2019) and ToMi (Le, Boureau, and Nickel 2019). Trott et al. 2022 evaluated LLMs on variations of the Sally-Anne false belief tasks, observing promising success rates, but still sub-human performance. Ullman (2023) and Shapira et al. (2024) demonstrated that even minor alterations to false-belief scenarios can significantly degrade model performance. Recently, those works have been extended through through procedural generation to consider a wider and more challenging set of Theory-of-Mind tasks (Gandhi et al. 2023; Sclar et al. 2024). Furthermore, Ruis et al. 2022 evaluated LLMs on problems which can only be resolved by understanding contextual information (implicatures), and observed a significant gap with human performance. LLMs' social competences have also been studied in interactive multi-agent interactions. Park et al. 2023 show a case-study where interacting LLM-based agents were able simulate complex social interactions such as organizing a party. Similar simulations were later conducted with more complex tasks (Chen et al. 2023a) and more agents (Yang et al. 2024). Zhou et al. 2023 present an evaluation suite for role-playing LLMs on interactions where they strive to achieve various social goals in cooperative and competitive settings.

Embodied Social Deep Reinforcement learning agents Recent work in Deep Reinforcement learning has produced agents capable of exhibiting various social behaviors in interactive embodied environments. To clarify, embodied, here is used in a more narrow sense, the agent is placed inside an interactive environment where it can move, interact with objects and it's observation space is often egocentric, but the body remains simplified and simulated as opposed to real-word robots studied in developmental robotics or HRI. Jaques et al. 2019 presented a multi-agent social dilemma environments requiring the emergence of cooperative behaviors through communication. Authors then showcased agents leveraging the maximization of causal influence as a way to foster cooperation. Ndousse et al. 2021 showed that, through the addition of an auxiliary next-state prediction task, DRL agents learning to perform navigation tasks among expert policies were able to learn to imitate social peers to overcome hard-exploration scenarios. Bhoopchand et al. 2022 presents a similar social-imitation approach able to scale to complex 3D environments and to imitate experts online, i.e. within episodes (rather than through gradient-based updates). Lee et al. 2021 showcase agents able to perform joint attention in cooperative tasks. They show that their intrinsic incentives towards joint attention helps to learn from experts through social learning. Franzmeyer, Malinowski, and Henriques 2021 present an intrinsic motivation mechanism able to foster altruistic helping in a multi-agent setting without requiring to know the true goal of other agents (the intrinsic signal is based on the maximization of other's choices). One of the objectives of the *SocialAI* project is to provide rich social scenarios in which to study and iterate on such learning systems within a broader range of social interactions. For example, The SocialAI school simplifies the design of generalization tests, which are crucial to differentiate heuristic policies from robust social proficiency, as demonstrated in Aru et al. 2022 in Theory of Mind experiments.

Multi-Agent Emergence of culture and communication Multi-agent systems are are an important subfield of interactive agents research exploring questions such as the emergence of communication (Lazaridou and Baroni 2020b; Moulin-Frier and Oudeyer 2020) and cooperation (Jaques et al. 2019). (Mordatch and Abbeel 2018) propose simple navigation environments with to study the emergence of grounded compositional language, Jaques et al. 2019 present multi-agent social dilemma environments requiring the emergence of cooperative behaviors through (non-verbal) communication. Nisioti and Moulin-Frier 2023 highlight the role of the environment by demonstrating how a changing environment leads to niche construction. An RL agent was shown to adapt (through social learning) to a new environment with an expert (Ndousse et al. 2021). The independent RL agent was trained in a multi-agent environment with various environmental constraints and an auxiliary loss. Similar experiments were also conducted at a larger scale (Bhoopchand et al. 2022). While multi-agent emergence of culture is an interesting research direction to study, the present work propose to focus on a complementary setup, arguably closer to human infants' challenges: How to design agents able to *enter* an already existing social world? Rather than negotiating new modes of communication, how to learn existing social norms?

Similar Tools for Fostering Research Similar tools have been constructed, often in the form of benchmarks, to support various research questions including instruction-following (Chevalier-Boisvert et al. 2019; Misra et al. 2018; Ruis et al. 2020), embodied question answering (Gordon et al. 2018; Das et al. 2017), collaboration given human demonstrations (Puig et al. 2021; Wan, Mao, and Tenenbaum 2022), or text-based social environments requiring dialogue (Urbanek et al. 2019; Ammanabrolu et al. 2020; Prabhumoye et al. 2020). In contrast to those, we focus on fundamental socio-cognitive abilities and do not aim to create a benchmark. By building on top of MiniGrid (Chevalier-Boisvert, Willems, and Pal 2018), we aim to provide a tool which can facilitate a diversity of research directions stemming from the outlined socio-cognitive abilities.

2.3 Cognitive science background

The following section introduces core concepts and experiments from the two developmental psychologists that inspired the SocialAI School: Michael Tomasello and Jerome Bruner.

2.3.1 Michael Tomasello - The Shared Intentionality Theory

We are born into a culture filled with cultural artifacts, symbols and institutions like language, social norms, tool industries, or even governments (Richerson and Boyd 2006; Tomasello 2019). These artifacts were not invented at once, rather they are a product of a series of improvements and modifications over many generations. Tomasello calls this powerful form of cultural transmission *cumulative cultural evolution*, and he argues that it is behind the most impressive human achievements (Tomasello 1999)

Cumulative cultural evolution is grounded in our socio-cognitive abilities (e.g. social cognition, cultural learning, communication), which enable us to learn, improve, and teach our culture (Tomasello 2019), i.e. *enter* a culture. Cultural artifacts inherited and learned in this process become the very core of our cognition. An example of this is language, which influences our cognition in many ways. For example, it defines how we categorize and construe the world, and enables a powerful form of social learning : learning from instructions (Tomasello 1999). This makes socio-cognitive abilities crucial, as their early development bootstraps both our social and asocial cognition (Herrmann et al. 2007).

Tomasello's *Shared intentionality theory* argues that human socio-cognitive abilities, such as communication and social learning, are transformed by two big developmental steps* : the emergence of *Joint intentionality* at around 9 months of age (the 9-month revolution), and the emergence of *Collective intentionality* at around 3 years of age (the objective/normative turn) (Tomasello 2019).

Joint intentionality emerges at around 9 months of age (Tomasello 2019). It enables children to form a *joint agent* (a dyadic "we") - they understand that they work with a partner towards the same joint goal. Children begin to view dyadic social interactions through a *"dual-level structure"*: a joint agent "we" on one level, and a personal "I" on another, i.e. we both understand that we both have separate roles ("I"), and that we work together towards the same joint goal ("we"). This enables them to take the perspective of others, which can also be done recursively - they are not only both attending to the same goal, they are also both attending to the partner's attention to the goal, and they both know that they both are doing so. This recursive thinking is also manifested in *socially recursive inferences*: recursively embedding one intentional or mental state inside another. When interpreting a pointing gesture, we make a recursive inference of what "*you* intend for *me* to think". For example, if we are looking for a ball together, and you point to a cupboard behind me. I should infer that you are drawing my attention to the cupboard to communicate that I should look for the ball in the cupboard.

Collective intentionality emerges at around 3 years of age (Tomasello 2019). It enables children to form a cultural *group-minded "we"*, which in comparison with a dyadic "we", represents an identity for a group. For

* These steps are referred to as *maturational capacities* to highlight that both the maturation and the exposure to relevant experience are required for those developmental steps

example, a child might enforce a social norm because "this is how *we*, in this culture, do things". Consequently, children begin to participate in conventions and norms, and to view things from the “objective” perspective.

These two developmental steps transform countless abilities, motivations, and behaviors. In this chapter, we focus on the following three developmental pathways: social cognition (sec. 4), communication (sec. 4), and social learning (sec. 4), as we consider them the most relevant for AI at the moment.

Tomasello argues that the 9-month-revolution and the objective/normative turn are uniquely *human* developmental steps enabling uniquely *human* socio-cognitive abilities. There has been a lot of debate regarding this hypothesis (De Waal 2016), and it still remains an open question. However, for the purpose of this chapter, the social proficiency of other great apes (or our last common ancestor with them) is not of primary importance. We find The Shared Intentionality Theory useful because it studies the questions regarding the development of core socio-cognitive abilities in very a systematic, extensive (covers a broad range of social abilities), and exact (is build upon a number of very clearly defined experiments) manner. We consider this a solid basis on which to structure AI research.

Social cognition

In this section, we discuss the development of the ability to coordinate perspectives and view things from the *objective perspective* (a perspective independent from any individual) (Tomasello 2019). The starting point is the ability to **imagine what another sees or knows**. The next step is the emergence of **joint attention (JA)** at around 9 months of age. Then, joint attention to mental content in the form of linguistic discourse results in **coordinating different perspectives with the *objective* perspective**

Imagining what others perceive The earliest instance of this is when six-month-olds follow the gaze of others (D’Entremont, Hains, and Muir 1997). It is important to note that, as compared to the later emerging ability to coordinate perspectives, this ability requires that only *one* perspective is processed at a time. Numerous studies have shown that both apes and children are capable of making such inferences (Hare, Call, and Tomasello 2001; Moll and Tomasello 2006). For example, Figure 2.2 shows an experiment from Hare, Call, and Tomasello 2001 where a subordinate and a dominant chimpanzee were presented with a competitive scenario : competing for food. Results showed that the subordinate chimpanzee attempted to eat the food only if it was hidden from the dominant one (this experiment motivated our experiments with inferring the other’s field of view in 2.5.6). This experiment was then extended to children who were presented with two toys: one observed by an adult and one occluded from him. When asked to help the adult find a toy, 24-month-olds passed the occluded toy (Moll and Tomasello 2006). These experiments, demonstrate that both children and apes are capable of inferring what a conspecific observes - i.e. they are able to infer another’s perspective.

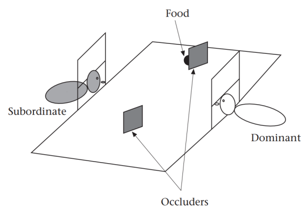


Figure 2.2: Sketch of an experiment from Hare, Call, and Tomasello 2001 showing that apes can infer the conspecific’s field of view. As the subordinate ape does not want to get into trouble, it will not steal the food from the dominant ape. In the experiment, the food was either occluded from the dominant ape or placed in plain sight. The subordinate ape ate the food only when it was occluded from the dominant ape. This shows that it was able to infer the dominant’s field of view.

Joint Attention Joint attention has been defined in various ways (Siposova and Carpenter 2019). To avoid confusion, we take the definition of joint attention from Tomasello 2019: joint attention consists of two aspects: *triangulation* and *recursiveness*. Triangulation refers to the child and the adult attending to the same external referent, and recursiveness refers to them both recursively being aware that they are both sharing attention. Joint attentions is also characterized by the dual-level structure: shared attention on one level, and individual perspectives on another. Joint attention enables children to process multiple perspectives at the same time, and they shortly start to align and exchange those perspectives.

In cognitive science, the emergence of joint attention is often studied by counting the child's alternating looks between the adult and referent object, or the child's attempts to initiate joint attention with the adult (Mundy et al. 1986). In Carpenter, Nagell, and Tomasello 1998 the amount of joint attention (number of joint attention episodes and their length) was measured in free play interactions between infants and their mothers. A steady rise in the amount of time spent in joint attention was observed in the period from 9 to 12 months.

Coordinating perspectives Once children reach sufficient linguistic competence, they start jointly attending to mental content in the form of linguistic discourse, and they begin to exchange and align perspectives of such content as well. Through linguistic discourse, children often encounter conflicting perspectives, which they are then pushed to resolve (e.g. one parent says it's raining outside, but another says it's not). They resolve those conflicts by learning to form an "objective" perspective - a bird's-eye-view perspective distinct from anyone's personal perspective - and coordinating the conflicting perspectives with it. For example, they are able to understand that the same object can, at the same time, "look like a sponge" (from their perspective) and "be a rock" (from the objective perspective) (Flavell, Flavell, and Green 1983). Tomasello argues that this can only be achieved once a child has passed through the second developmental step, that of collective intentionality, which enables them to form such a "perspectiveless" bird's-eye view perspective (Tomasello 2019).

Communication

For Tomasello, communication starts with **imperative gestures** for self-serving purposes (Tomasello 2019). An example of such a gesture is the child pulling the adult's hand, requesting them to pick them up. Such gestures always have the same imperative meaning, and they never refer to an external object. The 9-month revolution brings forth **referential communication** (pointing and pantomiming). The next step is the appearance of **conventionalized linguistic communication**. Linguistic communication gives rise to a myriad of different language uses, such as discourse or pedagogy.

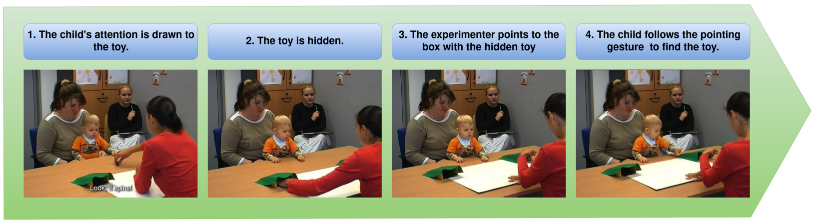


Figure 2.3: An experiment with children from Behne, Carpenter, and Tomasello 2005 studying their ability to infer the meaning of a pointing gesture. The child's attention is drawn to a toy. This toy is then hidden in one of the two boxes (the child does not know which one). The experimenter then points to one of the two boxes, and the child is able to infer this to mean that the toy is in that box.

Referential communication - The Pointing gesture Following the 9-month revolution, children start to communicate *referentially* - to an external referent (Tomasello 2019). This is primarily achieved through *pointing* and pantomiming. This is made possible by the emerging capacities for joint attention and recursive inferences. The pointing gesture is a powerful way of communicating, as the *same* gesture can be used to express many different meanings in many different scenarios, provided that the observer can correctly infer that meaning. This ability to infer the meaning is based on the newly emerging abilities of joint intentionality, most notably that of "socially recursive inferences" - to interpret a pointing gesture, we make a recursive inference of what "*you* intend for *me* to think". Hence, when someone directs our attention towards an object, we are able to infer the intended message.

Figure 2.3 depicts an experiment with children from Behne, Carpenter, and Tomasello 2005. First, the child's attention is drawn to the toy, which is then hidden in one of the two boxes. The experimenter then points to a box, and the child infers this to mean that the toy is in that box. 14-month-old children were able to successfully follow a pointing gesture to find the toy. In this scenario, the child makes the following recursive inference: the adult is helping by directing the child's attention to the box, and she wants the child to infer that the toy is in the box (this experiment motivated our experiments in section 2.5.2 and related experiments described in 2.5.6).

Linguistic communication Linguistic communication is based on the same principle as gestural referential communication: sharing attention to a referent and recursively inferring the intended meaning. However, linguistic communication in addition requires learning conventionalized means of reference, such as words or phrases. Where once was a single pointing gesture, now there is a complex grammar of gestures, with specific conventions assigned to each gesture. In Carpenter, Nagell, and Tomasello 1998 children's understanding of words steadily increased in the period after 9 months. This was measured by questioners given to their caretakers on regular intervals.

Tomasello argues that when language use first appears, children do not yet understand it as conventional, rather they use it as any other artifact or tool. It is only after the emergence of collective intentionality, when children start to understand and use conventions and norms, that they also begin to perceive language as such. This is evidenced by specific new ways in which they come to use and understand language. For example, when others break the rules of a game they protest by normative statements such as "No! It does not go like this!" (Wyman, Rakoczy, and Tomasello 2009). It is needless to say that language plays many important roles in children's development. Here we will outline just a few of countless possible examples. Language provides children with abstract constructions which gives them a new organized format for cognitive representation. Through discourse, children encounter many conflicting perspectives, which brings them to resolve those conflicts by forming the "objective" perspective. Finally, language opens up a new way of cultural learning - instructed learning - in which adults directly teach children "objective" truths about the world. Knowledge learned in that manner is easier to generalize (Butler and Tomasello 2016).

Cultural Learning

Human culture is characterized by a powerful form of cultural transmission called *cumulative cultural evolution* - inventions quickly spread and are improved by following generations (Tomasello 1999). These inventions spread at such a rapid pace that they are rarely forgotten. This is referred to as the *ratchet* effect (Tomasello, Kruger, and Ratner 1993) - as inventions are iteratively improved without *slippage*. This is made possible by advanced social learning abilities, such as imitation and instructed learning, but also by motivation not only to learn instrumental actions, but also to affiliate and conform. Tomasello prefers the term "Cultural learning" for learning motivated by cultural, and not only instrumental, motives.

The earliest form of cultural learning is the mimicking of facial expressions, which is observed even in neonates (Meltzoff and Moore 1997). Over the course of the first year, children begin to **imitate other's actions and goals**, and then, they begin doing so in ways which demonstrate their understanding of other's as intentional agents (Meltzoff 1995). Then, **role reversal imitation** appears as children begin to learn about the partner's role during a collaborative activity. The next big step in the development of cultural learning is learning from instructions - **instructed learning** (following the emergence of collective intentionality). It is based on the adults' motivation to teach children as well as on the children's ability to understand and learn from linguistic instructions. It has been shown that children understand knowledge acquired through instructions as objective truth, and generalize it much better than knowledge acquired by other means (Butler and Tomasello 2016). It is needless to say that in this way we acquire the most complex knowledge and skills such as reading or algebra. At around four years of age, children internalize this process, arguably, by reversing the roles (children take on the role of the adult giving instructions). This leads to a new type of self-regulation, a normative self-regulation based on conventions and norms.

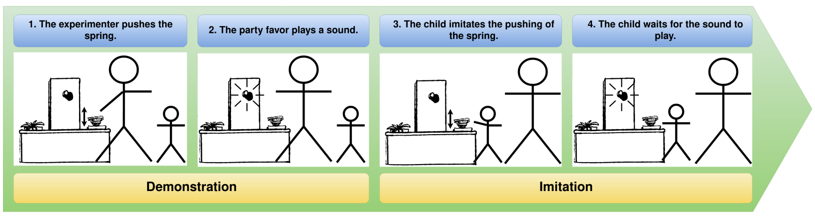


Figure 2.4: Depiction of an experiment from Carpenter, Nagell, and Tomasello 1998. The experimenter activates the party favor (sound) by pushing the spring, and the child imitates and waits for the sound. The sketch was taken and modified from Carpenter, Nagell, and Tomasello 1998

Imitation and Emulation Imitation and emulation learning both refer to observing a demonstration and learning from it. Imitation learning refers to the learning of means (actions), while emulation to the learning of ends (goals) of a demonstration (Whiten et al. 2004; Whiten et al. 2009; Tennie, Call, and Tomasello 2006). Refer to Whiten et al. 2009 for a discussion and taxonomy of imitative and emulative learning processes.

Figure 2.4 shows an experiment from Carpenter, Nagell, and Tomasello 1998 studying children's imitation abilities. In this experiment, the experimenter demonstrates an instrumental action (e.g. pressing a spring attached to a box) which activates the light on top of the box. The children repeated the instrumental action and looked at the light in expectation (this experiment motivated our experiments with imitation learning in 2.5.6). This type of learning emerges over the course of the first year - children reconstruct the outcome of others' actions. However, soon after this, children begin imitating in a way which demonstrates the understanding of other's goals. Children perform an action that an adult attempted, but failed to perform (Meltzoff 1995), and do not imitate accidental actions (Carpenter, Akhtar, and Tomasello 1998). Similarly, rational imitation appears. If a specific action was forced upon the demonstrator, the children recreate the result through more rational means (Gergely, Bekkering, and Király 2002). For example, in Gergely, Bekkering, and Király 2002 the demonstrator pressed a button with its head while having tied hands, and 14-month-olds responded by pressing the button with their hands.

Emulation is a type of social learning where the focus is on the outcome, and not on the actions performed (Wood, Bornstein, and Bruner 1989). In other words, the learning is about some property of the environment. The learner tries to recreate some observed outcome, in doing so they can, but don't have to, recreate the actions.

On the other side of this spectrum is *overimitation* - children repeat actions that are not relevant for the outcome. Children often prefer to not only recreate the outcome (as in emulation), but also do it in the same way as the adults (even if this requires doing additional unnecessary actions). For example, in Tennie et al. 2014 children were presented with a demonstration of a rice-pouring task. The experimenter performed a useless preliminary action before grabbing the rice. 4-year-old children responded by repeating both the useless and the necessary actions. It has been proposed that children overimitate to affiliate and conform for the purpose of in group bonding (Over and Carpenter 2013), but this remains an open question (Keupp, Behne, and Rakoczy 2013; Lyons, Young, and Keil 2007)

Role reversal Imitation Following the 9-month revolution, a new form of imitation appears - role reversal imitation. An example of this is when children respond to an adult tickling their arm, by tickling the adult's arm instead of its own (Carpenter, Tomasello, and Striano 2005). The emerging dual-level structure of joint intentionality enables children to understand, at the same time, the joint goal of a dyadic interaction, and the individuals' separate roles. This enables the child to reverse the roles of a collaborative activity, and learn about the partner's role from

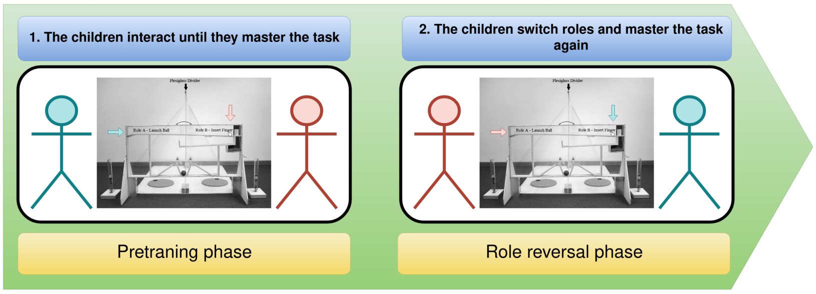


Figure 2.5: Depiction of an experiment on role reversal from Fletcher, Warneken, and Tomasello 2012. The task consists of two roles: one participant pushes a ball into the apparatus, and the other redirects it with their finger. The ball then pushes two marbles toward each of the participants. In the pretraining phase, children collaborate until they master the task (three consecutive successful trials). Then, in the role reversal phase, their roles are reversed and they master the task again. Total number of trials to master the task is compared between the two phases. Children, but not apes, needed less trials to master the task in the role reversal phase than in the pretraining phase.

only experiencing its own, which enables much faster transmission and acquisition of cultural practices and knowledge.

Figure 2.5 depicts an experiment with children and apes from Fletcher, Warneken, and Tomasello 2012. An apparatus is used where one participant pushes the marble, and the other inserts a finger to redirect the ball so that it falls to the correct location. Then, both participants get a reward. Children who previously played role A mastered role B in less trials than children who never played role A (this experiment motivated our experiments with role reversal in 2.5.3). In another experiment (Carpenter, Tomasello, and Striano 2005), children were asked to immediately reverse the role. An experimenter did some action on the child (e.g. poke the child and say "your turn") and the child responded with the same action on the experimenter (poked the experimenter back). These experiments show that children understand the separate roles and how each is relevant for the activity.

2.3.2 Jerome Bruner

This work is also influenced by the work of Jerome Bruner, most notably by his concepts of scaffolding (Wood, Bruner, and Ross 1976) and formats (Bruner 1985), which were recently reintroduced to AI as pragmatic frames (Vollmer et al. 2016; Rohlfing et al. 2016).

Formats (Pragmatic frames) simplify learning by providing a stable structure to social interactions (Bruner 1985). They are regular patterns characterizing the unfolding of possible social interactions (equivalent to an interaction protocol or a grammar of social interactions). Formats consist of a deep structure (the static part) and a surface structure (the varying realizations managed by some rules). An example of a format is the common peek-a-boo game (depicted in figure 2.6). The deep structure refers to the appearance and the reappearance of an object. The surface structure can be realized in different ways. For example, one might hide an object using a cloth, or hands; one might hide their face or a toy; one might do shorter or longer pauses before making the object reappear. Humans understand social interactions through such formats, and our social interactions are based on our ability to learn, negotiate, and use them. This research motivated our experiments with formats in section 2.5.6.

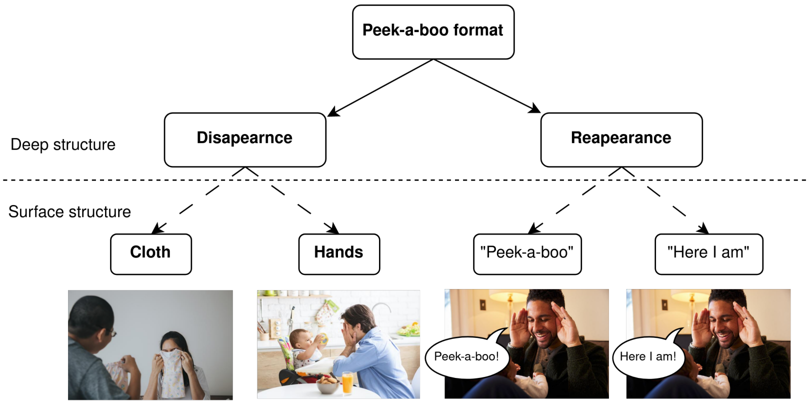


Figure 2.6: A simplified depiction of a format of the common children's game "peek-a-boo" . Formats consist of the deep structure (the static part), and the surface structure (varying realization managed by some rules). In this example, the deep structure is the disappearance and the reappearance of the adult's face, and the surface structure refers to different ways of hiding the face and signalizing its reappearance.

Another relevant concept is scaffolding (Wood, Bruner, and Ross 1976), which is very similar to Vygotsky's zone of proximal development (Vygotsky and Cole 1978). This concept is also related to Csikszentmihalyi's theory of flow (Csíkszentmihályi 1999), with the distinction that in flow the learning is not necessarily mediated by a caretaker. Scaffolding is a process through which the adult bootstraps the child's learning. The adult controls aspects of a task which are currently too hard for the child, i.e. reduces the degrees of freedom in the task. Then the scaffold is gradually removed as the child is ready to take on more aspects of the task, until they can solve the task alone (without scaffolding). An example is a child constructing a pyramid with the help of an adult (Wood, Bruner, and Ross 1976). At first, the child is not even focusing on the task, and the adult tries to get its attention to the task by connecting blocks and building the pyramid in front of them. Once the child is able to focus on the task, the adult starts passing the blocks to the child to connect. In the next phase, the child is grabbing blocks by itself, and the adult is helping through verbal suggestions. Then, only verbal confirmations are needed to guide the child. Finally, the child can construct the pyramid by itself. We can see how the adult observes the child and gradually transfers parts of the task to the child (removes the scaffold). Through this process the caretaker enables the child to master a task they would not be able to master alone. This research motivated our experiments with scaffolding in 2.5.4.

2.4 The SocialAI school

The SocialAI school is a tool for building interactive environments to study various questions regarding social competence, such as "What do concepts, such as social abilities and motivations, outlined by developmental psychology mean in the scope of AI?", "How can we evaluate their presence in different agents?", "What are their simplest forms and how can agents acquire them?"

To construct SocialAI, we rely on a set of key experiments and studies from developmental psychology, which were used to outline the most important abilities, motivations and developmental steps in humans. From the work of Tomasello, we focus on developments before and around the age of 9 months (we believe it is important to address those before more complex ones relating to development of 3-year-olds, see section 2.3.1). We study the following relevant concepts from three developmental pathways: social cognition (inferring other's perception and joint attention), communication (referential communication through the pointing gesture and the beginning of conventionalized communication through simple language), and cultural learning (imitation and role reversal imitation). From the work of Bruner, we study the concepts of formats and scaffolding (see section 2.3.2). Using The SocialAI school, we construct environments and conduct experiments regarding all of those concepts.

SocialAI, which is built on top of Minigrid (Chevalier-Boisvert, Willems, and Pal 2018), includes a *customizable parameterized* suite of *procedurally* generated environments. We implement this procedural generation with a tree-based structure (the parametric tree). This makes it simple to add and modify new environments, and control their sampling. All the current environments are single-agent and contain a scripted peer. The agent has to interact with the peer to reach and eat an apple. This setup enables a controlled and minimal representation of social interactions. To facilitate future research, SocialAI was made to be very easy to modify and extend. It is completely open sourced, and we hope that it will be useful to the community to study the questions regarding social intelligence in AI. An online interactive demo (`https://huggingface.co/spaces/flowers-team/SocialAISchool`) enables to explore different environments, parameters and sampling trees in the SocialAI School.

The remainder of this section is organized as follows. First, section 2.4.1 describes technical details such as the observation and the action space. Then, section 2.4.2 introduces the parameter tree and explains how it can be used to sample environments. Finally, section 2.4.3 describes two environment types, which were used in case studies in section 2.5. In the Appendix, we discuss one additional environment type (Appendix A.1.4) and additional case studies (Appendix A.1.6).

2.4.1 Parameterized Social Environments

The environments in SocialAI are implemented as one-room gridworlds. In all environments, the task of the agent is to eat the apple, at which point it is rewarded. The reward is diminished according to the number of steps it took the agent to complete the episode. The episode ends when the agent eats the apple, uses the *done* action, or after a timeout of 80 steps.

The agent's observation space is shown in Figure 2.7. This multi-modal observation space consists of the full dialogue history, and a 7x7x8 tensor corresponding to the 7x7 grid in front of the agent. Each cell is encoded by six integers representing the object type, color, and some additional object-dependent information (e.g. is the door open, point direction, gaze direction, etc). Refer to figure A.10 in the Appendix for a list of all objects.

The agent acts in the environment through a multi-modal action space, which consists of 6 primitive actions (*no*, *turn left*, *turn right*, *go forward*, *toggle*, and *done*) and a 4x16 templated language. The agent also has the option not to speak, which is implemented with an additional binary output from the agent. Refer to Appendix A.1.1 for details about the architecture of the agent.

All environments, unless otherwise stated, contain a scripted social peer, and the task can only be solved by interacting with this peer (for which socio-cognitive abilities are needed). A social peer observes the world in the same way as the agent does (as a grid in front of it), and it also observes the agent's utterances. Their action space consists of primitive actions for movement, pointing, and the *toggle* action. The peer can also communicate with words and sentences. As the peer is scripted, there are no constraints on the language it can utter (it is not constrained to a templated language). The language it uses depends on the environment, which defines which sentence the peer will utter at which point. The peer is represented in the agent's observation by 7 integers depicting their: object type, position, color, type (cooperative or competitive), gaze direction, point direction, and the last executed primitive action. The peer's gaze and point directions are represented relative to the agent (e.g. 1 - to the left of the agent). The pointing direction can also be set to 0, which signifies that the peer is not pointing. Figure 2.8 shows an example of an environment with the corresponding encoding of the peer. The agent (red) and the scripted peer (purple) are making eye contact - the peer and the agent are in the same row or column and their gazes meet frontally. In this example, the scripted peer is also pointing to the blue box.

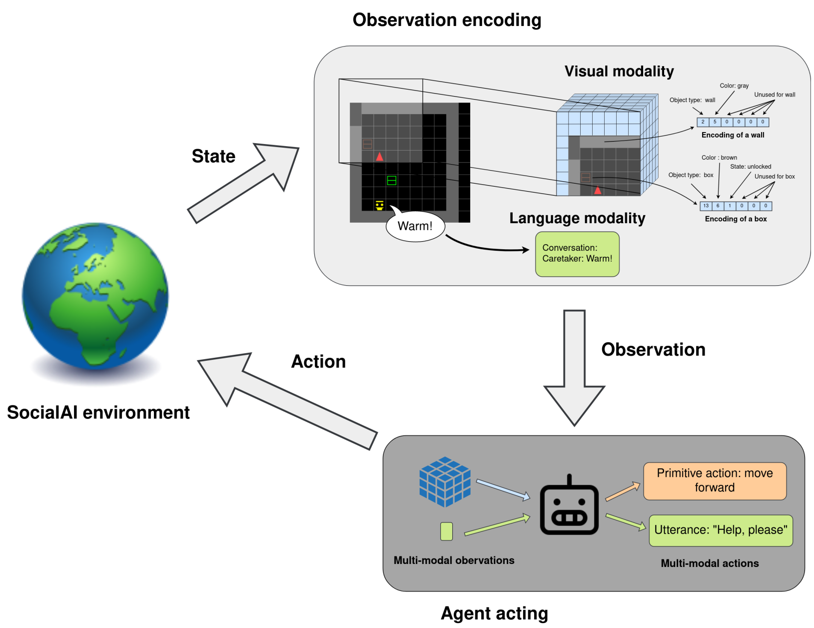


Figure 2.7: Workflow of an agent acting in the SocialAI school. The environment generates a state, which is represented as multi-modal observations: a 7x7x6 tensor and the full dialogue history. The agent acts through a multi-modal action space consisting of primitive actions and utterances.

The SocialAI environments are parameterized, and those parameters define the social dimensions of the task. In other words, parameters define which socio-cognitive abilities are needed to solve the task. For example, depending on the Environment type parameter, the peer can give information, collaborate with the agent, or be adversarial. In the case of the peer giving information, additional parameters define what is the form of this information (linguistic or pointing).

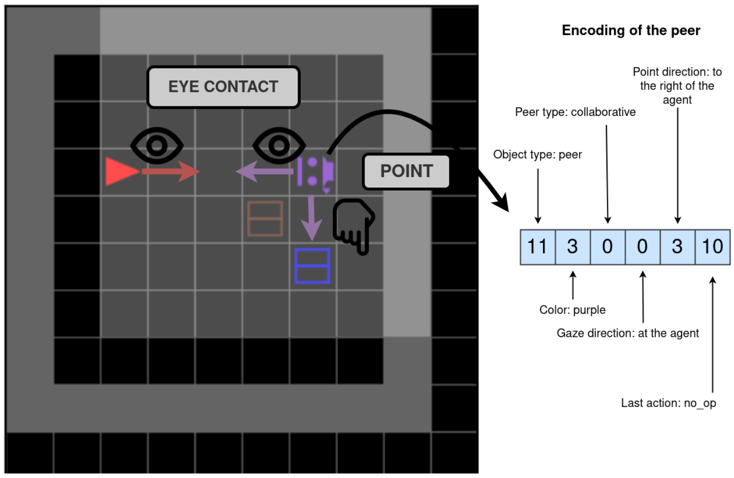


Figure 2.8: A depiction of a peer and its encoding. The agent and a peer are in eye contact, and the peer is pointing to the blue box. To the right is an encoding of the peer. The encoding contains information about the peer, e.g. the gaze and point direction. Refer to figure A.10 in the Appendix for a list of all objects.

2.4.2 Parameter tree

SocialAI enables the creation of many parameterized environments, and those parameters are implemented as nodes in a parameter tree. A parameter tree is a structure through which the experimenter can easily define which parameters (and their values) can be sampled. An example of such a tree can be seen in Figure 2.9. The standard procedure is that an experimenter defines a parameter tree. Then each episode begins with the sampling of a new parameter set from this tree. Once a parameter set has been sampled, an environment is created, and the agent placed inside.

An example of sampling parameters from a parameter tree is shown in Figure 2.9. There are two kinds of nodes: parameter nodes (rectangles) and value nodes (ovals). Parameter nodes correspond to parameters, and value nodes corresponds to possible values for those parameters. Sampling proceeds in a top-down fashion, starting from the root node. In all our experiments, Env_type parameter node is the root. Sampling from a parameter node selects one of its children (a value node), i.e. sets a value for this parameter. This can be done by uniform sampling over the node's children, or by prioritized sampling with a curriculum. Once a value node has been chosen, the sampling continues through it to all of its children (parameter nodes). In other words, setting a value for one parameter, defines which other parameters (the value node's children) need to be set. In our codebase, it is simple to create such trees, and add additional parameters and environments. In the following sections, we explain the most relevant parameters. Refer to figures A.14, A.15 and A.16 in the Appendix for examples of parametric trees.

2.4.3 Environment types

The most important parameter is the environment type - Env_type. This parameter node is always the root node. We implemented three different environment types: InformationSeeking, Collaboration, and AdversarialPeer. A parameter tree doesn't necessarily contain all three, this choice entirely depends on the type of experiment one wants to conduct and, most often, only one of type will be present in a tree. For example, Figure 2.9 shows the tree with only the InformationSeeking environment type.

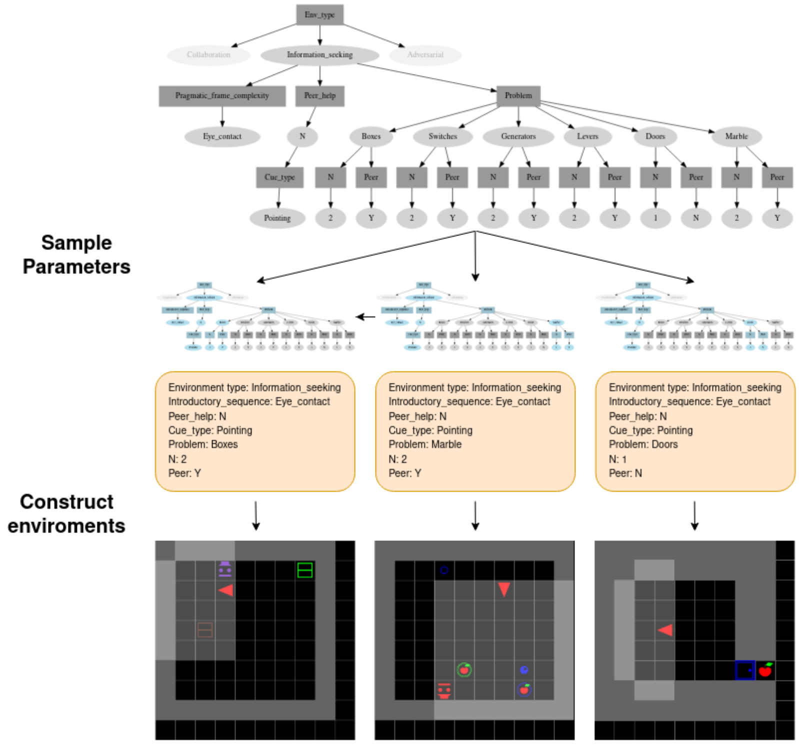


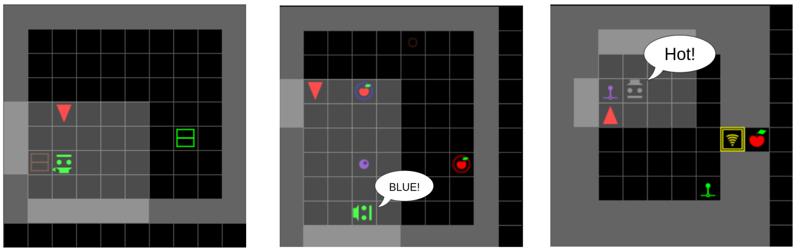
Figure 2.9: An example of procedural environment generation using tree-based parametric sampling. There are two kinds of nodes: parameter nodes (rectangles) and value nodes (ovals). Parameter nodes require that one of its children (a value node) is selected. Value nodes require that sampling progresses through all of its children (parameter nodes). In this tree, all parameter nodes except "Problem" have only one child. This means that only the Problem parameter can be set in different ways. We show three examples of parameter sampling, and the three environments constructed from those parameters. An online interactive demo `https://huggingface.co/spaces/flowers-team/SocialAISchool` enables to explore different environments, parameters and sampling trees.

This tree was used to study understanding of the pointing gesture in section 2.5.2. In the rest of this section, we describe the InformationSeeking and the Collaboration environment types. We describe the AdversarialPeer type in the Appendix A.1.4.

Information Seeking type environments This environment type will be used in case studies regarding communication, joint attention, and imitation learning. In figure 2.10 we can see examples of InformationSeeking type environments.

The general principle of this environment type is as follows. The agent is rewarded upon eating the apple, which is hidden. The apple can be accessed by interacting with an object. The Problem parameter defines which objects will in the environment. There are six different problems: boxes, switches, marble, generators, doors, or levers. Different objects make the apple accessible in different ways. For example, opening the box will make the apple appear at the location of the box, while pulling the lever will open the door in front of the apple. A distractor can also be present (if N is set to 2). A distractor is an object of the same type as the correct object. If the distractor is used, both objects are blocked and the apple cannot be obtained in this episode.

To find out which object is the correct one, the agent must interact with the scripted peer. This interaction starts with the agent introducing itself. The way in which the agent should introduce itself is defined by the Introductory sequence parameter. We define the following four values:



(a) A scripted peer pointing to a box. The agent needs to open the red box.

(b) A scripted peer uttering the color of the correct generator. The agent needs to push the marble onto the blue generator.

(c) A scripted peer hinting the distance to the correct lever ("Hot" means very close). The agent needs to pull the purple lever to open the door.

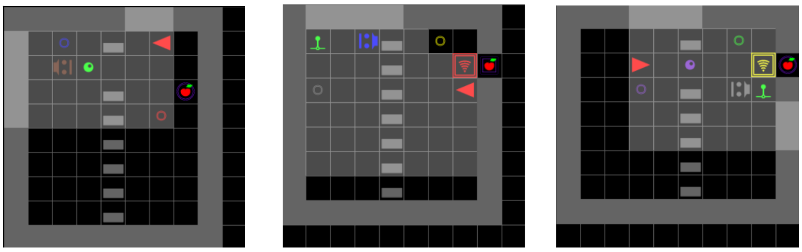
Figure 2.10: Examples of Information-Seeking type environments, in which agents learns to find hidden apples using textual or non-verbal communication with social peers.

No, Eye_contact, Ask, Ask-Eye_contact. For the value No, no introduction is needed and the peer will give information at the beginning of the episode. In most of our experiments, we will use the value Eye_contact. For this value, the scripted peer will turn to look at the agent and wait for the agent to look at it. The agent must direct its gaze directly towards the scripted peer. An example of an established eye contact can be seen in figure 2.8. For the value Ask, the agent needs to utter "Help, please". The agent does so using templated language, by selecting the "Help, *X*" template and the word "please". A full grammar of the language is given in table A.1 in the Appendix. Finally, the Ask-Eye_contact value is a combination of the previous two. It requires that the agent utters "Help, please" during eye contact.

Once the agent introduces itself, the Help parameter defines the peer's behavior. If it is set to Y the peer with obtain the apple, and leave it for the agent to eat. Alternatively, it will give cues to the agent about which object to use. The nature of this cue is defined by the Cue type parameter. We define four different values: Pointing, Language Color, Language Feedback, and Imitation. For the Pointing type, the peer will move to a location from which it can unambiguously point (e.g. the same row) and point to the object. For the Language Color type, the peer will say the color of the correct object. For the Language Feedback type, the peer will hint how close the agent is to the correct object. Every step, the peer will say "Cold", "Medium", "Warm" or "Hot", depending on how close the agent is to the correct object. For example, "Cold" means that the agent is far from the object, and "Hot" that it is right next to it. For the Imitation type, the peer will demonstrate the use of the correct object. The peer will use the correct object, obtain the apple, and eat it. Then it will reset the environment to its initial state.

For the purpose of analyzing the agent's behavior more thoroughly, Information seeking environments can also be created without the distracting object, i.e. in their asocial versions. This can be achieved by setting parameter Peer to N and parameter N to 1. The asocial version of an information seeking environment contains no distractor, and no peer, i.e. the agent just needs to use the only object in the environment.

Collaboration type environments This environment type will be used to study the ability of the agent to reverse roles. It consists of collaborative activities with two clearly defined roles. Environments are separated into two halves (corresponding to different roles) by a fence over which the agent can see, but which it cannot cross. If both roles are fulfilled



(a) The MarblePass problem with the agent in role B. The peer pushes the marble to the right and then the agent pushes it further to the purple *marble generator*. This makes two apples appear on the blue and red platforms.

(b) The LeverDoor problem with the agent in role B. The peer opens the red door by pulling on the green lever. This enables the agent to go through the door and activate the purple generator This makes two apples appear on the gray and yellow platforms.

(c) The MarblePush problem with the agent in role A. The peer opens the yellow door using the green lever. Then the agent pushes the marble through the door to the purple *marble generator*. This makes two apples appear on the purple and green platforms.

Figure 2.11: Examples of Collaboration type environments, in which agents must learn cooperative strategies with a (scripted) peer to achieve two-player puzzles.

correctly, two apples will become accessible (one on each side of the fence).

The most important parameters are Role and Problem. The Role parameter defines in which role to put the agent. The Problem parameter defines the collaborative activity, of which we implemented seven: DoorLever, MarblePush, MarblePass, Boxes, Switches, Generators, Marble. In DoorLever one participant opens the door by pulling the lever and the other passes through them, and activates the generator (generating two apples). In MarblePush one participant opens the door by pulling the lever, and the other pushes a marble through them. This marble activates the *marble generator* upon contact with it. In MarblePass one participant pushed the marble to the right side of the room, and then the other pushes it towards the *marble generator*. In the remaining four problems, one participant is presented with two boxes of different colors. The other participant is presented with two objects of the same colors as the two boxes and of the type defined by the problem parameter (e.g. two generators). First, the participant that was presented with boxes opens one box (an apple will be in both). After this, to obtain its apple, the other participant must use the object of the same color as the opened box. In Figure 2.11 we can see examples of Collaboration type environments.

Like the information seeking environments, collaboration environments can also be instantiated in their asocial versions. This can be achieved by setting the Version parameter to Asocial. The peer is not present in the environment, and the environment is initialized so that the task can be solved alone. For example, in MarblePass the marble is already on the right side of the room, so the agent just has to push it towards the *marble generator*.

2.5 Experiments

In this section we demonstrate how the SocialAI school can be used to conduct diverse experiments motivated by cognitive science. We present a set of case-studies inspired by theories and studies described in section 2.3. To facilitate future research, SocialAI was made to be very easy to modify and extend. It is completely open sourced, and we hope that it will be useful to the community to study the questions regarding social intelligence in AI.

The remainder of this section is organized as follows. In section 2.5.1 we describe the agents used in case studies with reinforcement learning (RL). In section 2.5.2 we evaluate the generalization of socially recursive inferences by RL agents to new contexts - pointing in a new context. In section 2.5.3 we show how an experiment from cognitive science can be recreated in the context of AI - we study the transfer of knowledge from one role to another, i.e. role reversal. In section 2.5.4 we study how an RL agent can be made to learn a complex task by changing the environment (scaffolding) rather than the agent. Finally, in section 2.5.5 we show how SocialAI environments can be easily transformed to pure text to study LLM-based interactive agents. We conduct many additional case studies, which are in the interest of readability briefly outlined in section 2.5.6 and discussed in detail in Appendix A.1.6. These additional case-studies regard linguistic communication, joint attention, meta imitation learning, inferring the other's field of view, and formats (pragmatic frames).

2.5.1 Baselines

In our case studies with RL we use a PPO (Schulman et al. 2017) agent as depicted in Figure 2.7. The multimodal observation space consists of a 7x7x6 tensor (vision) and the full dialogue history (language). The multimodal action space consists of 6 primitive actions (*no_op*, *turn left*, *turn right*, *go forward*, *toggle*, and *done*), and a 4x16 templated language. The architecture of the agent is taken from Hui et al. 2020 and adapted for the multimodal action space with an additional output head (see Appendix A.1.1). This additional head consists of three outputs: a binary output indicating if the agent will speak, and outputs for the template and the word to use.

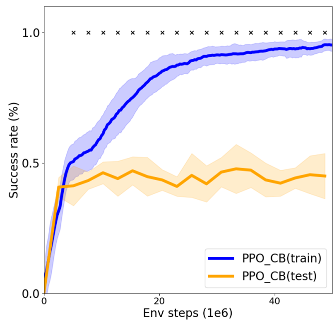


Figure 2.12: The Pointing experiments. We study if an RL agent is able to infer the meaning of a pointing gesture. The agent was trained on five different problems, and on the asocial version of the Doors problem (only one door and no peer in the environment). The Figure compares the success rate (mean +/- std over 8 seeds) on the training environments with the evaluation on the testing environment - the social Doors problem (two door and the peer pointing to the correct door). The cross marks depict statistical significance ($p = 0.05$). We can see that the agent achieves high performance on the training environments, but it is not able to infer the meaning of a pointing gesture in a new context (the social Doors task)). Figure 2.10a shows an example of a SocialAI environment with pointing.

In a set of pilot experiments (see Appendix A.1.3), we proposed two episodic count-based exploration bonuses. They estimate the diversity of observations in an episode and give reward proportional to that diversity. CBL (linguistic) exploration bonus uses the number of different words, and CB (vision-based) exploration bonus uses the number of different encodings observed. Refer to Appendix A.1.2 for details. We compared them to other exploration bonuses including RND (Burda et al. 2018) and RIDE (Raileanu and Rocktäschel 2020). Our vision-based exploration bonus ("CB") performed best on the tasks in which language is not used, and its linguistic variant "CBL" performed best in environments with the peer giving linguistic cues. For this reason, in case studies in sections 2.5.2 and 2.5.3 we use the "PPO-CB" exploration bonus. The case study in section 2.5.4 requires raw PPO for the purposes of the study, and the one in section 2.5.5 uses LLMs as agents. In Appendix A.1.6, we also use CB, and CBL in case-studies in which the peer provides linguistic feedback.

2.5.2 Understanding the pointing gesture

This experiment is motivated by a study of children's ability to understand pointing gestures (Behne, Carpenter, and Tomasello 2005), discussed in Section 4. We study if an RL agent (with a visual count-based exploration bonus) can infer the meaning of a pointing gesture, and generalize this ability to new situations (infer the new meaning of a pointing gesture in a new context). This kind of generalization is relevant because the power of inferring pointing gestures is based on being able to infer it's meaning to *new* referents based on *new* social contexts.

Here we will present an example using the Doors problem (all other problems can be approached in the same way). We decided to focus on the Doors problem as it is the simplest, and hence, if no generalization is observed it is safe to assume we would not have observed it on harder problems as well. The testing environment consists of two doors and the peer that points to the correct door to open to get access to an apple. The agent is trained on five problems each with different objects (e.g. Switches, Levers, Marble, Generators, Boxes), and on the *asocial* version of the Doors problem (i.e. only one box and no peer). Training on the asocial version enables the agent to learn how to use a door, which is a prerequisite for generalization of the pointing gesture to an environment with two doors. The agent is evaluated on the Doors problem in the social setting (two doors and a peer pointing to the correct one). The agent needs to combine the knowledge of how to use a door (learned on the asocial version of that problem), with inferring the meaning of the pointing gesture (learned on the other five problems), and generalize that to a new scenario where the peer points to a door. To succeed, it needs to do pragmatically infer the intended meaning of the point (a socially recursive inference). Refer to section A.1.5 in the Appendix for details.

Figure 2.12 shows the success rate of the agent on the training environments ("PPO_CB(train)") and its evaluation on the evaluation environment (PPO_CB(test)). We can see that while the agent easily solves the training environments (with the success rate of 95.2%), it fails to generalize. It reaches the success rate of 45.2%, which corresponds to randomly guessing the object to use. These results demonstrate that the agent can learn to infer the meaning of a pointing gesture in a familiar context, but cannot generalize to new social contexts. These results motivate future research on how an agent can be endowed with abilities for such combinatorial generalization, a potential solution could leverage LLMs.

Appendix A.1.6 presents two experiments in which the peer, instead of pointing, provides linguistic cues for the color and for the proximity of the correct object. As in the pointing experiments, we observe that while PPO agents master the training environments, they fail to generalize to a new context.

2.5.3 Role reversal imitation

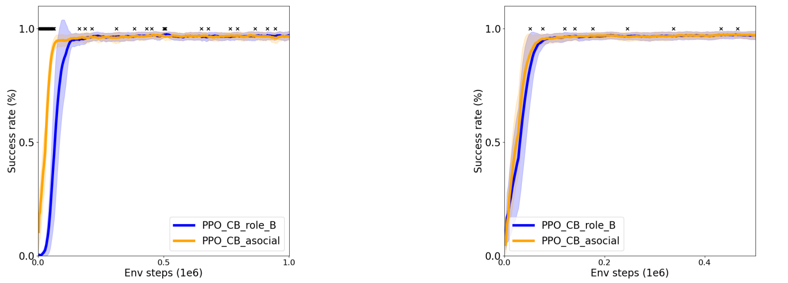
In this experiment, we study the role-reversal capabilities of an RL agent (with the visual count-based exploration bonus). We explore to what extent can an agent learn about the partner's role from playing its own.

In doing so, we also show how a cognitive science experiment can be recreated in the scope of AI. In Fletcher, Warneken, and Tomasello 2012 apes and children were trained on one role (role B), and then tested on how long it took them to master the opposite role (role A). Results showed that children, but not apes, master role A faster than the control group (not pretrained). These results imply that children learn about the opposite role just from playing their own, i.e. they see the interaction from a bird's eye perspective. We study the following two questions: 1) How much do RL agents learn about the partner's role during a collaborative activity? 2) Does increasing diversity in the training (training on more tasks in both roles) enable the agent to learn more about the partner's role?

We conduct this study on the MarblePass task. This task consists of two roles: one participant pushes the marble to the right side of the environment (role A), from where the other can push it to the a generator, which generates apples (role B). We aim to assess how much the agent learns about the opposite role (role A), from training in its own (role B). Following Fletcher, Warneken, and Tomasello 2012 we measure the sample efficiency of fine-tuning agents to the test role. Unlike in Fletcher, Warneken, and Tomasello 2012 it is not sufficient to compare an agent pretrained on the training role with an unpretrained agent. Even if the agent pretrained on the training role learns nothing about the testing role, it would still learn about environment dynamics and one would expect it to learn faster than the unpretrained agent. For this reason, we compare with an agent pretrained on the asocial version of the training role. In this version, the agent obtains reward in the same way as in the social version, but no peer is needed - the agent and the marble are placed on the right side of the environment and the agent has to push the marble towards the generator. Therefore, this agent learns all about the relevant environment dynamics, but not about the specific collaborative activity. This agent correponds to the control group in Fletcher, Warneken, and Tomasello 2012.

We conduct two experiments: *single* and *group*. In *single* experiments, the agents are trained only on one task : role B and the asocial version of the MarblePass problem. In *group* experiments, both agents are also trained both roles of all additional six collaborative problems (a total of 13 environments). In other words, we compare the agents pretrained in the four following ways: 1) experimental (*single*): pretrained only on role B of the MarblePass problem, 2) control (*single*): pretrained only on the asocial version of the MarblePass problem, 3) experimental (*group*): pretrained on role B of the MarblePass problem, and on both roles of all other problems, 4) control (*group*): pretrained on the asocial version of the MarblePass problem, and on both roles of all other problems. Refer to Appendix A.1.5 for additional details.

How much do RL agents learn about the partner's role during a collaborative activity? Figure 2.13a shows the success rate of fine-tuning to role A of the MarblePass task. It compares the experimental and the control conditions of the *single* experiments. It is interesting to note that the agent pretrained on the asocial version ("asocial") masters role A of the task slightly faster than the agent pretrained on role B of the task ("role_B"). This implies that, not only, the agent does not learn anything useful about the peer's role, but pretraining on role B actually makes it harder for the agent to learn about role A. We believe that this is because, during training in role B, the agent learns to first wait for the peer, while in the asocial version it pushes the marble right away. As, in role A, the agent pushes the marble right away too, we believe this makes it slightly easier for the asocially pretrained agent to adapt to the new role. In other words, from an egocentric view the asocial version is closer (than role B) to role A. This shows that the RL agent, rather than understanding the interaction from a bird's-eye perspective, finds the simplest way to solve the task.



(a) *Single* experiment: learning role A given pretraining on role B (1 environment).

(b) *Group* experiment: learning role A given pretraining on role B and 6 other two-roles tasks (13 environments).

Figure 2.13: Role reversal imitation experiments. We study to what extent is an RL agent able to transfer knowledge from one role of a collaborative activity to another. Figure shows the success rate of fine-tuning to role A (mean ± std over 8 seeds), the cross marks depict statistical significance ($p = 0.05$). We compare a PPO agent pretrained on role B ("role_B") to that pretrained on the asocial version of the environment ("asocial"), which learns only about the environment dynamics. Agents pretrained on role B do not master role A faster than asocially pretrained agents, implying that the RL agents do exhibit role reversal capabilities.

Does training on additional problems enable the agent to learn more about the partner's role? Figure 2.13b shows the success rate of fine-tuning to role A of the MarblePass task. It compares the experimental and the control conditions of the *group* experiments. Here we can see that there is no significant difference in sample efficiency. We can make two observations from this. First, as the socially pretrained agent was less sample efficient in the *single* experiments, we can conclude that pretraining on many tasks reduces overfitting on role B. And second, as this agent is not more sample efficient than the asocially pretrained baseline, we can conclude that this agent does not learn anything useful about the peer's role either.

These results imply an interesting avenue of research into how agent's attention can be directed to the partner's role and the birds-eye-view of the activity.

2.5.4 Scaffolding

In this section, we study the concept of scaffolding (see section 2.3.2 for details). We show how modifying the environment can make it easier for the agent to learn a complex task, i.e. we explore if a scaffolded environment can help an agent learn more complex interaction sequences (formats). This can be seen in contrast to the standard approach, where the environment is kept fixed and the agent improved (e.g. with an exploration bonus).

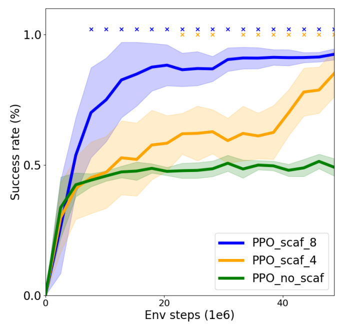


Figure 2.14: The scaffolding experiment. The comparison of agents trained on multiple environments of varying difficulty to that trained on an unscaffolded environment. The Figure show success rates on the testing environments (mean ± std over 8 seeds) and the cross marks depict statistical significance ($p = 0.05$) with respect to the "no_scaf" baseline. Only the scaffolded agents ("scaf_4" and "scaf_8") solve the environment, and the scaffolding with eight difficulty levels is more sample efficient.

For this reason, here we use a PPO agent without an exploration bonus. From the AI perspective, scaffolding can be seen as analogous to curriculum learning (Bengio et al. 2009; Portelas et al. 2020). In curriculum learning, the task is made gradually more complex, enabling the learner to gradually acquire it part by part. Scaffolding refers to the caretaker taking a large part of the task on itself, and then gradually, as the learner becomes more proficient, transferring parts of the task to the learner until the learner can do the whole task by themselves.

The environment is similar to the one in section 2.5.2 with small changes. We evaluate on all six problems (instead of one) in the social version. Instead of pointing, the peer gives linguistic cues for how close the agent is to the target object (e.g. "Hot" for very close), and these cues are given after a more complex introductory sequence (established eye contact and the utterance of "Help, please"). The agent is trained in two phases. In the first phase, the agent is trained on environments with different complexity. After reaching a set success rate, the training goes to the second phase in which the agent is trained only on the six testing environments. We compare two types of scaffolding: "scaf_4" and "scaf_8", which define the environments in the first phase. The agent denoted by "scaf_4" is trained on four different introductory sequences (requiring or not requiring eye contact and the utterance). This agent is trained on 18 different environments (six problems, four sequences). The "scaf_8" agent is also trained with those four different options. In addition, the peer can help in two different ways: linguistically hinting to the object or interacting with it and leaving the apple for the agent to eat (36 environments). The easiest environments on which the "scaf_8" agent is trained do not require an introduction and the peer leaves the apple for the agent (the agent just goes to the apple and eats it). The hardest ones require the introduction with both the utterance and eye contact and include the peer linguistically hinting to the object. Those hardest environments constitute the testing set. See Appendix A.1.5 for more details.

Figure 2.14 compares the success rate of the agents trained with the two scaffolding types ("scaf_4" and "scaf_8") to that of an agent trained only on the six testing environments ("no_scaf"). We can see that only the scaffolded agents solve the testing environments, and that the agent with a more detailed scaffolding ("scaf_8") solves the environment faster. These results show that scaffolding enables the agents to learn more complex formats, and that a more thorough scaffolding further improves the efficiency. In future work, more advanced scaffolding could be explored, ex. based on learning progress (Oudeyer and Kaplan 2007) or other surrogate objectives (Portelas et al. 2020).

2.5.5 Large language models as interactive agents

Large language models (LLMs) are staring to be used in various tasks (Brown et al. 2020; Devlin et al. 2018; Zhang et al. 2022; Ouyang et al. 2022a), including to control interactive agents (Yao et al. 2022; Carta et al. 2023). In order to be able to study LLMs as interactive agents, SocialAI school enables the parsing of visual grid observations to pure text, i.e. to TextWorlds (Côté et al. 2018).

We use two environments: AsocialBox and ColorBoxes. In AsocialBox there is a box in the environment and the agent has to open it to get the apple. In ColorBoxes there are two boxes and the peer. At the beginning of the episode, the peer says the color of the correct box (the box with the apple). When testing for generalization on the ColorBoxes environment, we create in-context examples in environments with other objects (e.g. doors, levers) and in the asocial version of the Boxes problem (analogous to the training environments in Section 2.5.2). To generalize, an agent must infer the meaning of the peer's utterance in a new context (to select the correct box) and combine this with the knowledge of how to open a box (from the asocial version).

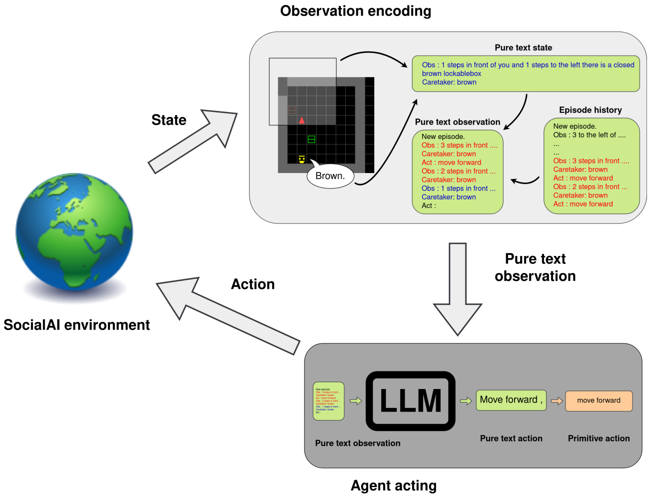


Figure 2.15: An example of how a language model can be used as an interactive agent in SocialAI. A state is parsed into a pure text observation and combined with previous two observations and actions. This is, appended to the in context examples, is used as prompt for the LLM. The agent generates the text which is then matched (as case insensitive substring) with the list of possible actions. The matched action is executed in the environment.

A language model acts by generating text, given some textual prompt and the observations are parsed into pure text as shown in Figure 2.15. In our experiments, the prompt contains the following: the in context examples, the last three steps (observations and actions) of the current episode, and the action query ("Act :"). We manually create expert trajectories to be used as in context examples - 6 episodes for the AsocialBox environment, and 5 for ColorBoxes (the full in context examples are given in Appendix 12). The model then generates the textual continuation of this prompt. [†] If one of the available actions ("turn left", "turn right", "move forward", "toggle") is a substring of the generated text, the action is executed and the environment generates the next observation. However, if no action was matched to the generated text, the "no_op" action is executed (the agent does not act this step). The executed action and the new observation are then added to the prompt.

We compare six different large language models: the open-source multilingual "bloom-560m" (Scao et al. 2022) (560M), and five models from the GPT (Brown et al. 2020) family "text-ada-001" (estimated to be 350M [‡]), "text-davinci-003" (175B parameters), "gpt-3.5-turbo-instruct-0913", "gpt-3.5-turbo-0613", and "gpt-4-0613". We also compare with a random baseline, which samples a random action each step. We evaluate these models on a fixed test set of 10 environments for AsocialBox and 20 environments for ColorBoxes, with a time limit of 15 steps.

Table 2.1 shows that, on the AsocialBox environment, the best GPT models (gpt-4 and davinci-003) achieve a high performance (100% success rate), despite only observing six expert trajectories. On ColorBoxes, gpt-4 is the only model to achieve high performance (75%). This model escapes the

[†] We generate 3 tokens for GPT models, and 3 words for bloom.
[‡] https://blog.eleuther.ai/gpt3-model-sizes/

local optimum of 50% (randomly choosing a box to open), these results imply that the model uses the given social cue (the peer's utterance of the color). As gpt-4 was the only model to do so, we test only this model on generalization. The model reaches a performance of 55%, which implies that the model doesn't generalize to a new social context - it randomly chooses a box to open.

The motivation of this experiment was only to show how LLM-based agents can be studied in SocialAI. Therefore, more detailed experiments and analysis are needed to reach stronger conclusions. Even though the environments used in this case study are simpler than those RL case studies (only the Boxes problem, and no introductory sequence), we find it impressive that such performance is achieved from observing only a few expert trajectories: six for AsocialBox and five for ColorBoxes.

Table 2.1: Comparison of LLM-based agents on two SocialAI environments parsed into pure text (see Figure 2.17). The best model (gpt-4) reached the success rates of 100% on AsocialBox, and 75% on ColorBoxes. The score of 75% suggests that the model is levering the peer to choose the correct box. When tested for generalization this model reached 55% success rate implying it is not able to generalize to a novel object. These experiments demonstrate how LLM-based agents can be used in the SocialAI School. While more detailed analysis is needed to reach stronger conclusions, the performance is impressive given that the models observed only six (for AsocialBox) and five (for ColorBoxes) expert trajectories. We are confident that with more advanced LLM-based methods better performance can be achieved.

	gpt-4	gpt-3.5-turbo	gpt-3.5-turbo-instruct	ada-001	davinci-003	bloom-560m	random
AsocialBox	**100%**	90%	90%	90%	**100%**	10%	0%
ColorBoxes	**75%**	5%	25%	0%	15%	5%	5%
ColorBoxes (gen.)	**55%**						

Follow-up Experiments with Modern Instruction-Tuned LLMs Between the time the experiments above were conducted and the writing of this thesis there has been substantial improvements in the capabilities of LLMs. To account for this progress, we conducted new set of experiments using a more recent model - GPT-4.1, released in April 2025. In addition to general performance improvements, a notable development has been the widespread adoption of instruction-tuned models, optimized for chat-style interactions. Current LLMs allow users to directly convey goals and environment dynamics via natural language instructions, rather than relying solely on in-context learning. Leveraging these advancements, we adopted a simplified setup for GPT-4.1: instead of providing in-context examples, we supplied explicit instructions that describe the structure and objectives of the SocialAI environments. An example prompt for the ColorBoxes environment is shown in Figure 2.16. We also incorporated Chain-of-Thought prompting (Wei et al. 2022), encouraging the model to "think step-by-step" before selecting an action. Responses were generated using a temperature of 0.2 and a top_p value of 0.9. For each task, we created a test set of 30 environments and repeated each experiment using three random seeds on the same test set.

We first evaluated whether GPT-4.1 can successfully use the provided instructions to control an agent in SocialAI environments. To do this, we

```
You are an agent in a gridworld.
You can turn around to see all objects in the environment.
You can open a box by standing directly in front of it and toggling it.
You can eat an apple by toggling it.
You succeed upon eating an apple.
An apple can be inside a box.
Actions: ['move forward','done','turn left','turn right',toggle]
Think step by step and finish your response with "Action: <action>", where <action>
is exactly the name of the action you want to take.
```

Figure 2.16: Instructions given to GPT-4.1. Instructions describe the dynamics of the ColorBoxes environment, but they do not give any information pertaining to the social peer or how to interpret it's utterances.

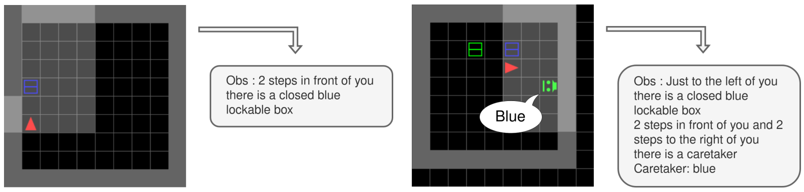
created six distinct instruction sets - one for each of the six core problems: Boxes, Doors, Levers, Generators, Switches, and Marble, with instructions modified to describe the corresponding environment dynamics. We evaluated GPT-4.1 on the asocial versions of these problems (e.g. an environment consisting of a single box containing the apple). The results of these experiments are shown in Table 2.2 under the "Asocial" column. We observe that the model solves the Boxes and Doors problems with high success rates (1.00 and 0.99, respectively). Performance is somewhat lower on Levers (0.79) and Switches (0.59), while the Generators (0.34) and Marble (0.01) tasks remain more challenging. While we believe that higher performance could be achieved through more advanced setups - such as incorporating image-based observations or applying more sophisticated prompt engineering - our goal is not to optimize performance through heavy engineering. Indeed, this related to Chapter 3 where we study how LLM behavior can greatly depend on small changes in the prompt. Hence, we continue with the current framework and focus on the four problems with higher success rates: Boxes, Doors, Levers, Generators.

Next, we investigate whether the LLM demonstrates behavior consistent with correctly inferring the meaning of the caretaker's utterance in a novel context—for example, understanding that "blue" refers to the correct box to open. Table 2.2 presents the results for the social versions of the four selected problems: Boxes, Doors, Levers, and Generators. In the *standard* condition, we reuse the same instruction prompts as in the asocial setup (e.g. the instructions in Figure 2.16). These instructions describe the environment's physical dynamics (e.g., how to open a box by toggling it), but make no mention of the caretaker or how to interpret its utterances. To assess the extent to which the model's behavior reflects an understanding of the caretaker's cues, we introduce two control conditions. In the *expert* control, we augment the prompt with an explicit instruction explaining the meaning of the caretaker's utterance—for example: "The caretaker helps you by telling you the color of the correct box to open". This represents the upper bound of performance and behavior consistent with correctly interpreting the caretaker's utterance. In contrast, the *mask* control represents the lower bound: the caretaker's utterance is entirely removed from the agent's observation space, preventing the model from using this information at all. By comparing performance across these three conditions, we can estimate the extent to which the agent's behavior is consistent with correct interpretation of the caretaker's utterance. We quantify this with $\alpha = \frac{standard-mask}{expert-mask}$.

Table 2.2 shows that the value of α varies considerably across tasks. the agent exhibits behavior that is at least partially consistent with correctly inferring the caretaker's utterance, though a clear gap remains compared to the *expert* control. The highest consistency is observed on the Doors task, with an α score of 0.82. In contrast, performance on the Switches problem is comparable to that in the *mask* control, with overlapping standard error intervals—suggesting that the agent is not leveraging the caretaker's cue in this setting. Overall, we observe that the extent to which the agent is able to interpret social inferences greatly depends on the task. For instance, it is possible that the agents lower mastery of using switches prevents it from efficiently inferring social cues in the context of using switches. This is interesting given that the difficulty of the inference does not vary between the considered task, i.e. "The Caretaker helps you by telling you the color of the correct box/door/lever/switch to open/open/activate/activate.". This highlights how it is extremely important to test LLM-based systems in many different contexts, which is also argued in Chapter 3.

Table 2.2: Follow-up LLM results. GPT-4.1 exhibits behavior to an extent consistent with correctly inferring the social cue, but a performance gap remains - one whose size appears to depend on the problem at hand

Problem	Asocial	Mask	Standard	Expert	α
Boxes	1.00 ± 0.00	0.56 ± 0.02	0.71 ± 0.01	0.86 ± 0.01	0.52
Doors	0.99 ± 0.01	0.58 ± 0.01	0.92 ± 0.01	1.00 ± 0.00	**0.82**
Levers	0.79 ± 0.06	0.22 ± 0.02	0.36 ± 0.03	0.50 ± 0.04	0.48
Switches	0.59 ± 0.06	0.28 ± 0.03	0.22 ± 0.05	0.39 ± 0.03	-0.50
Generators	0.34 ± 0.04	-	-	-	-
Marble	0.01 ± 0.01	-	-	-	-



(a) The AsocialBox environment **(b)** The ColorBoxes environment

Figure 2.17: Two environments used in the experiments with large language models. The observations are parsed into pure text.

2.5.6 Additional experiments

We refer interested readers to Appendix A.1.6 for details on a complementary set of case studies, which we briefly outline in this section. As mentioned in the pointing case study (section 2.5.2), we performed analogous experiments to study whether the agent can leverage linguistic cues instead of the pointing gesture (Appendix A.1.6). We obtained analogous results: while the RL agents master the training environments, they fail to generalize to new context.

In Appendix A.1.6, we study joint attention as defined by Tomasello (see section 2.3). Environments feature a peer providing cues both inside and outside joint attention. Informative cues are only given inside joint attention (after completing the introductory sequence), while misleading random cues are given outside joint attention. In our experiments, the RL agent was unable to sufficiently discriminate between those cues to solve the task.

Appendix A.1.6 presents a case-study on the acquisition of an (in-episode) imitation learning mechanism with RL. From the AI perspective, this can be seen as social meta-learning: the agent acquires (through gradients) the imitation learning mechanism, which is used during the episode to learn a instrumental action on a new object. Similarly, from the recently emerging

LLM perspective, this can be seen as in-context learning. This study is motivated by an experiment from cognitive science in which children showed such imitation abilities (Carpenter, Nagell, and Tomasello 1998). Experiments showed that RL agents are not able to acquire a learning mechanism which would enable them to learn how to use a completely new object at test time.

In Appendix 12 we test the agent on its ability to infer the peer's field of view. The agent is rewarded for eating the apple under the condition that it was not observed by the peer at that moment. We show that the agent partially infers the peer's field of view, but is still not able to match the upper performance bound.

Finally, in Appendix 12 we study the acquisition and use of formats as defined by Jerome Bruner (section 2.3.2), i.e. protocols of social interactions. Agents were trained on tasks in which cues can be obtained from a peer after a more complex introductory sequence (Ask_Eye_-Contact). The results show that, while an RL agent trained without the exploration bonus was unable to learn that introductory sequence, the agent with a linguistic count-based exploration bonus was. This results can be interpreted in tandem with the scaffolding case study (section 2.5.4) in which an RL agent without an exploration bonus is able to learn the most complex introductory sequence, given training in a scaffolded environment. Therefore, the acquisition of complex formats can be achieved either through changing the learner or the environment.

These additional case studies show further examples of interesting research questions that can be explored with the SocialAI school.

2.6 Discussion

Following contemporary research in developmental psychology, this work presents and studies a wider set of socio-cognitive abilities than those usually studied in the field of AI. The motivation of this work is to introduce those concepts to AI and motivate related research. We present an introduction to Michael Tomasello's and Jerome Bruner's theories of socio-cognitive development. Following these theories, we outlined a set of key socio-cognitive abilities and concepts for AI: social cognition (inferring other's perception and joint attention), communication (referential and early conventionalized communication), cultural learning (imitation and role reversal imitation), scaffolding, and formats.

We introduce the SocialAI school - a tool simplifying the research of core socio-cognitive abilities. We show how the SocialAI school can be used to easily create environments studying the outlined concepts and various questions inspired by developmental psychology. With RL agents, we conduct experiments regarding the pointing gesture, scaffolding, and role reversal (by recreating an experiment from developmental psychology). We demonstrate that, by using SocialAI to parse environments into text, Large Language Models be easily studied as well. In the Appendix, we present many additional studies concerning other concepts and abilities including: linguistic communication, joint attention, imitation learning, inferring others' field of view, and formats. Our experiments demonstrated the diversity of studies that can be conducted with the

SocialAI school, highlighted the limitations of standard RL agents, and showed that while large language models exhibit behavior to an extent consistent with correctly inferring the social cue, a performance gap remains - one whose size appears to depend on the problem at hand.

Overall, this chapter calls for research into social abilities of AI agents that is strongly grounded in developmental psychology. To that end, it provides a list of key concepts that we deem to be relevant for AI at the moment, and that can serve as signposts for directing future research. Furthermore, it presents a tool to foster the research on those concepts.

Limitations and Future Work In this chapter, we outline and discuss several concepts from developmental psychology – mostly regarding the development before and around 9 months of age – which we found to be most relevant for AI at the moment. Even among this restricted set it is not reasonable to aim for an exhaustive introduction. As such, several socio-cognitive concepts are either discussed very briefly (e.g. conformity, social norms, instructed learning) and a lot of others are not mentioned (e.g. morality, fairness, sense of self). We leave their analysis for future work. Furthermore, while we argue that the work of Tomasello and Bruner provides an interesting framework to guide AI research in social skill acquisition, many other perspectives and theories could have been considered, e.g. Erik Erikson (Erikson 1993), Alison Gopnik (Gopnik and Meltzoff 1997), or Cecilia Heyes (Heyes 2019).

Similarly, as the present work merely represents a first step towards socially proficient artificial learners, many technical dimensions were simplified. In particular, we refrain from free form language dialogues and consider simple templated language. Likewise, we do not use human or trained peers, but scripted peers (which enables to isolate social abilities). Rather than implementing rich 3D visual worlds with continuous actions, we use grid-worlds with discrete primitive actions. While such simplifying assumptions affords tractable studies while maintaining enough social complexity to model and isolate various social challenges, a richer and more naturalistic set of environments could be created following the recent advances in LLMs. Scripted peers could be replaced with LLM-based agents which could communicate in natural language, give a variety of direct or indirect social cues. This could enable a larger diversity and complexity of social games such as collaboration, competition, discussion, etc. Future extensions could include adapting SocialAI environments for use with image-based inputs to enable experimentation with vision-language models (VLMs), or even extending them into 3D settings or real-world settings. Given the recent introduction of LLMs into robotics (Zeng et al. 2023), we could imagine recreating SocialAI tasks and studying concepts outlined in this chapter with physical robots, which could interact with other robots or humans. Such directions would enable the study of sociality in AI, that is both strongly grounded in psychology and considering very natural and realistic interactions.

Given recent works showcasing the importance of Automatic Curriculum Learning in "asocial" DRL (Parker-Holder et al. 2022; Portelas et al. 2020), an interesting direction for future work would be to study whether this can also be observed in SocialAI. Our short case study on the importance of scaffolding (sec. 2.5.4) suggests a positive impact, although we restricted our analysis to simple expert curricula. An important challenge will be to design curriculum methods able to leverage the hierarchical structure of SocialAI's parametric tree, rather than the usual low-dimensional flat spaces of task-encoding parameters (predominant in the literature).

Large language models (LLMs) are present in many branches of artificial intelligence. A promising avenue of future research is the application of language models to interactive agents (Andreas 2022a). In this chapter, we studied LLMs only on simple environments with simple methods: prompting the model with a few expert trajectories, and providing a list of descriptions of the environment. While this approach showed impressive performance a gap with expert performance still remains. These experiments should be revisited with more powerful methods such as fine-tuning or more complex versions chain-of-thought such as Three-of-Thoughts (Long 2023) or an agentic architecture (Wang et al. 2024a). Such methods may enable more sophisticated social inference, potentially leading to improved performance on several of the case studies presented in this thesis—particularly those involving generalization to novel scenarios. Moreover, these approaches could be evaluated across a broader range of tasks, both within the SocialAI School and in external setting.

The avenues discussed in this section provide an interesting path, grounded in developmental psychology, towards building and evaluating agents capable of *entering* a human culture.

From psychology - Part 1

In this section, we discuss how we leveraged and adapted developmental psychology research in Part I. This mostly pertains to research done by Michael Tomasello and Jerome Bruner.

Concepts We outlined many concepts and abilities from the theories of Michael Tomasello and Jerome Bruner. We proposed those concepts as signposts to direct AI research. While some concepts have already been thoroughly studied in AI (e.g. imitation learning, inferring the other field of view), others have not (e.g. such as socially recursive inferences, role reversal). Furthermore, the extensive theory of Michael Tomasello coupled with research from Jerome Bruner, enables us to outline a structure of a wide range of abilities covering large portion of social cognition based on which many future research directions emerge.

Methodology The experiments conducted with humans and apes provided the basis and inspiration for many environments and experiments in this chapter. Here, we discuss two examples from our RL experiments: inferring the meaning of a pointing gesture, and role reversal. To study the ability to infer the meaning of a pointing gesture we mimicked the experimental setup from Behne, Carpenter, and Tomasello 2005 with several relevant adaptations. Given the well known problems with generalization in AI, we added additional tasks that use different objects to be used for training. Due to the RL agents being trained from scratch, our setup required additional training environments which provided the agents with the opportunity to learn about the environment dynamics and about the pointing gesture (those were not needed with humans as it is assumed that they already encountered the pointing gesture and that they know how to open a box). To study role reversal, we mimicked the experimental setup from Fletcher, Warneken, and Tomasello 2012. To adapt for training from scratch, To separate social knowledge (about the opposite role) and knowledge about environment dynamics and locomotion, additional the control condition was modified to include pretraining on the asocial versions of the task (such pretraining is not needed with humans as it is assume that they already know about environment dynamics and locomotion). Similarly, we created additional versions of role reversal scenarios to provide the agent with the opportunity to observe additional two-role interactions. These examples, show how psychological methodology can be transferred to AI by making various adaptations particularly by adding additional controls and evaluation settings.

Part II

Characterizing a culture

3 Large Language Models as Superpositions of Cultural Perspectives

What is this chapter about? This chapter focuses on the question "How can we characterize and evaluate socio-cultural aspects of AI systems?". In particular, we focus on one out of many possible aspects of cultural expression - value and personality expression. Recently, there has been an increased use of psychological questionnaires to study LLMs, for instance examining their expression of values, traits, and cognitive abilities. This chapter can be seen as primarily presenting a positioning regarding that practice. We raise caution regarding such studies and discuss potential pitfalls of using the "LLM-as-a-participant" metaphor and viewing LLMs as having, for instance, *a* personality, *a* set of values, or *a* cognitive ability. Instead, we argue that an LLM could be seen as a *superposition of perspectives* expressing different values and personality traits. Unlike humans, who tend to maintain relatively stable values and personality traits across contexts, LLMs display extremely context-dependent behavior that varies with the perspective induced by the prompt. In our experiments, we use established psychological questionnaires (PVQ, VSM, IPIP) to study how expressed values and personality traits change based on perspectives induced by different contexts. We show that LLMs express different values when those are (implicitly or explicitly) implied in the prompt, and that LLMs express different values even when those are not obviously implied (demonstrating their complex context-dependent nature). When comparing to results from existing human studies, we observe that LLM-expressed values change more despite being induced by smaller context changes (conversation topic compared to years of development in human studies). We likewise introduce the concept of perspective controllability, which refers to a model's affordance to adopt various perspectives with differing values and personality traits. We examine the controllability of different LLMs (GPT-4, GPT-3.5, OpenAssistant, StableVicuna, StableLM) and compare the effectiveness of various perspective induction methods. We conclude by discussing the broader implications of our work and outline a variety of associated scientific questions. In particular, we argue that psychological questionnaires can serve as valuable tools if applied to LLMs with caution, and that special attention must be paid to how the measured constructs—whether cognitive abilities, values, or personality traits—may vary in response to even subtle changes in context.

Timeline: The research discussed in this chapter was done in 2023 in sole first authorship. The LLM field has drastically evolved since the end of 2023, with the release of many new models which were not tested in this chapter.

Contribution: 1st authorship

Scientific output: Grgur Kovač, Masataka Sawayama, Rémy Portelas, Cédric Colas, Peter Ford Dominey, and Pierre-Yves Oudeyer (2023). 'Large language models as superpositions of cultural perspectives'. In: *arXiv preprint arXiv:2307.07870*

3.1 Introduction

As large language models (LLMs) become better at mimicking human language, human natural tendency toward anthropomorphism fosters perceiving them as entities with values, personalities, knowledge, or abilities. This perspective is also to an extent reflected in some research approaches that apply psychological methods (originally designed to study human individuals) to directly probe LLMs as participants in a psychological experiment (Miotto, Rossberg, and Kleinberg 2022; Li et al. 2022a; Binz and Schulz 2023a). While these approaches constitute the first examples of using psychological questionnaire with LLMs and have as such contributed valuable insights, we suggest that the metaphor of the "LLM as individual" may not fully capture the nature of language models.

Here, using extensive experiments, we present evidence against this metaphor, in particular by highlighting **unexpected perspective shift effects**: changes in context (i.e. prompts) that are apparently unrelated to values or personality actually cause significant and unpredictable changes in the model's expression of values and personality. Thus, values and personality traits expressed by LLMs are strongly context-dependent in ways that vastly differ from humans. To detect these effects, we measure expressed personal values (Schwartz 2012), cultural values (Hofstede and Bond 1984) and personality traits (Goldberg 1999a) with three questionnaires developed and validated in the human psychology literature. While humans tend to demonstrate stable measures in these tests across contexts (Goldberg 1990; Schwartz 1992b) and over their lifetime (Sagiv et al. 2017), we show that the same measures computed from the answers of a single LLM are significantly affected by variations in context that seem to be totally orthogonal, e.g. short conversations about unrelated topics, or different textual formats of the questions. These results raise questions about the possibility to make certain general scientific conclusions when using psychological questionnaires with LLMs: they were in fact designed assuming human properties which do not apply to LLMs.

We propose a new metaphor: "**LLM as a superposition of perspectives**". A perspective is conceptualized as a context from which a model is required to simulate a behavior. A prompt induces a perspective with its underlying values, personality traits, abilities and knowledge - a perspective that will causally impact the observed behavior. Let us consider a quantum mechanics parallel: a particle is described to be in a superposition of states, and the process of measuring collapses the particle into one observed state. Analogously, an LLM can be described to be in a superposition of perspectives, and prompting as inducing a single observed perspective. Crucially, we argue that it is impossible to use an LLM without inducing a perspective. For instance, the mere choice of which language to use influences the exhibited cultural values (Arora, Kaffee, and Augenstein 2023). This phenomenon can be traced back to the training of LLMs, leveraging a wide diversity of texts, each written from a different perspective (e.g. of an individual or a community) associated with different values, knowledge and cultural background (Arora, Kaffee, and Augenstein 2023; Hershcovich et al. 2022). Fine-tuning LLMs from human feedback (Christiano et al. 2017; Ouyang et al.

2022b) aims at aligning the model with "human values", but it also involves a plurality of perspectives, each label being again coming from a different person with a different background (Rame et al. 2023). However, we would like to clarify that this metaphor is meant merely as an intuitive conceptualization to better explain our argument. Primarily, we aim to show that methods used in many papers studying the capabilities of LLMs using psychology questionnaires provide results that should call for very careful interpretations, and we propose extensions of these methods to form a better picture of the LLMs' properties.

This new metaphor enables us to study how perspectives change in both unexpected and expected (controllable) ways, and raises new questions: can we force LLMs to take a target perspective? What are good perspective induction methods and is this model-dependent? Are some models less sensitive to unexpected perspective shift effects? How can we measure the sensitivity of language models to perspective inductions? We make first steps towards answering these questions by introducing the notion of *perspective controllability*, a measure of the capacity of a given perspective induction technique to induce a target perspective for a given language model. Using this concept, we systematically study four induction techniques over 16 models and report our findings.

Finally, we will see that discarding the old metaphor could invite the reinterpretation of recent studies that aim to characterize the values, personality traits, social skills or moral values of LLMs using tools developed to measure attributes of human psychology (e.g. Miotto, Rossberg, and Kleinberg 2022, Stevenson et al. 2022, Li et al. 2022a)

To summarize, the main contributions of this chapter are as follows:

- Introduction of the *unexpected perspective shift effect* and presentation of strong evidence for its existence: simple context variations unrelated to values and personality lead to significant changes in their expression by LLMs. These changes are bigger than changes in humans caused by much more extreme circumstances (e.g. years of development).
- A systematic comparison of six LLMs along three types of value stability: mean-level change, rank-order, and intraindividual (ipsative).
- The rejection of the "LLM as individual" metaphor and its replacement with the "LLM as a superposition of perspectives" metaphor, more apt at capturing the nature of LLMs.
- The introduction of the notion of *perspective controllability* to characterize the ability of a perspective induction method to induce a target perspective in a given LLM.
- A systematic study of the perspective controllability of four induction methods and 16 LLMs.
- A discussion of the impact of this metaphor shift can have on the interpretation of recent studies.

3.2 Related Work

There has been a lot of research studying large language models using tools from psychology. These works have conceptualized LLMs in various different ways. For instance, one way is to use the "LLM as an individual" metaphor (often implicitly) and simply treat the LLM as a human participant in a study. Binz and Schulz 2023a evaluate a finetuned LLaMa model on tasks studying decision making from descriptions and experience. Kosoy et al. 2023 evaluate a LaMDa model on a battery of classical developmental tasks and compare its performance with the one of human children's. Stevenson et al. 2022 compare GPT-3 to humans on the Alternative Uses Test (Guilford 1967) test for creativity. Li et al. 2022a evaluate LLMs (GPT-3 and FLAN-T5) on two personality tests: Short Dark Triad (Jones and Paulhus 2014) and Big Five Inventory (John and Srivastava 1999). Miotto, Rossberg, and Kleinberg 2022 estimated GPT-3's personality and culture with HEXACO (Ashton and Lee 2009) and HVS (Schwartz, Breyer, and Danner 2015) questionnaires. Although not directly using psychological questionnaires, there is a body of work estimating LLMs' Theory of Mind through textual representations of standard False-belief tasks (Kosinski 2023; Sap et al. 2022). Binz and Schulz 2022 also make this "LLM as a participant" assumption and evaluate GPT-3 on a number of cognitive tests from psychology. These works constitute some of the earliest attempts to study LLMs using psychological questionnaires, and as such, they have been highly valuable to the research community. The perspective and metaphor introduced in this chapter can be seen as a natural progression and extension of those foundational efforts.

Another common conceptualization is that of "LLM as a population". In this metaphor, an LLM encodes a population of personalities, and a prompt induces a specific personality to exhibit. Andreas 2022b propose to see an LLM not as an agent, but as a modeling various agents related to the text. LLMs were shown to model beliefs, desires, and intentions of the potential writer and of other agents mentioned in the text. Shanahan, McDonell, and Reynolds 2023 introduce the metaphor of role-playing, where an LLM chooses a character to role-play based on context. While this metaphor is close to ours, a key difference is that a *perspective* encompasses a wider scope than a character. For example, a perspective of a "log file" (generated by an automatic process) or of a code (written by thousands of people) is not the same as a character. Cao et al. 2023 study cultural expression by prompting the model with personalities from different countries. Arora, Kaffee, and Augenstein 2023 study cultural expression of smaller language models by inducing perspectives of speakers of different languages through translations of a questionnaire. Salewski et al. 2023 induce perspectives of different experts to improve performance, and Deshpande et al. 2023 induce perspectives of famous people to show that toxicity can increase as a consequence. Aher, Arriaga, and Kalai 2022b replicate studies with humans by varying names of protagonists essentially placing the model in the perspectives of humans from different backgrounds. Similarly, Argyle et al. 2023 replicate data from human studies by prompting the model with backstories of real human participants in those original studies. In this work, we aim to build on this body of research by analyzing not what values or traits are expressed in a single context, but how those can change over contexts.

Some recent studies investigated disadvantageous effects of context on the behavior of LLMs. Griffin et al. 2023 show that exposing an LLM to some statements increases its perceived truthfulness at a later time, and Perez et al. 2023 demonstrate the tendency of models to repeat back the user's answer. We focus on context induced changes that are neither intuitive and common in humans, i.e. those which would be hard to predict. Li et al. 2016 highlight the problem of inconsistency in personas simulated by language models. The most similar work to ours is a concurrent paper studying the coherence of simulated personas in general (as opposed to our specific focus on personal value stability in simulated individuals and populations). That work proposes to increase the similarity of LLaMa-70b-chat model's answers before and after simulated conversations by reweighting the instruction's attention weights (Li et al. 2024).

The second part of this section studies how models' values and personality expression can be controlled, i.e. the expected perspective shifts due to context changes. There has been some recent work on this topic as well. Santurkar et al. 2023 study expressed opinions by placing the model in the perspective of different demographic groups. Jiang et al. 2023b focus on the control of the expression of personality traits using a special prompting technique and human evaluation.

3.3 Methods

This chapter aims to uncover the existence of *unexpected perspective shift effects*, i.e. how context can impact the values and personality traits expressed by LLMs in unwanted, *unexpected* ways. Furthermore, we are also interested in measuring the *perspective controllability* of different language models, the extent to which one can intentionally induce a perspective, i.e. an *expected* perspective shift. To this end, we need: 1) a way of measuring values and personality traits expressed by LLMs, 2) a way of exposing LLMs to various contexts in a controlled manner and 3) a way of measuring the *controllability* of any given LLM.

Measuring values and personality traits using questionnaires from human psychology. We measure the personal values, cultural values and personality traits expressed by LLMs using three questionnaires developed in the human psychology literature.

Personal values – Following Schwartz 1992b, we consider 10 personal values grouped into four categories: *openness to change* (hedonism, self-direction, stimulation), *self-enhancement* (achievement, power), *conservation* (conformity, tradition, security), and *self-transcendence* (universalism, benevolence). We measure scores for each of the 10 values on a 6-point Likert scale using the *Portrait Values Questionnaire* (PVQ) (Cieciuch and Schwartz 2012).

Cultural values – Following Hofstede and Minkov 2013, we measure cultural values along six dimensions: power distance, individualism vs. collectivism, masculinity vs. femininity, uncertainty avoidance, long-term orientation vs. short-term orientation, and indulgence vs. restraint. We measure scores for each of the 6 dimensions on a 5-point Likert scale using the *Values Survey Module* (VSM) questionnaire (Hofstede 2013).

Personality traits – The Big Five personality traits include five major dimensions of human personality: neuroticism, extraversion, agreeableness, conscientiousness, and openness to experience. We measure scores for each personality trait on a 6-point Likert scale using the Goldberg's IPIP representation of Costa and McCrae's NEO-PI-R Domains (Costa and McCrae 2008; Goldberg 1999b). Details for all questionnaires can be found in Appendix Section B.1.

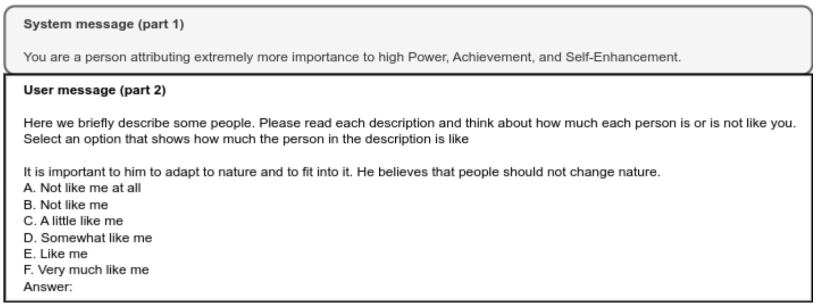


Figure 3.1: Inducing a perspective for the PVQ questionnaire. We aim to induce the target personal values of *self-enhancement* (*power* and *achievement*) using a 2nd person perspective transmitted via the system prompt of language models. We then compute the answer of the model conditioned on that perspective for a question from the PVQ questionnaire. This process is repeated independently for all questions of the questionnaire and 50 different permutations of the answers order.

Evaluating a language model with a given context. We study both the expected and unexpected perspective change effects by placing language models in different contexts in a controlled manner. Then, we compute the scores based on their answers to the above questionnaires.

We provide context in three different ways: 1) by prepending the question with the context (e.g. article, conversation), 2) by adding the context to the *system message* content (OpenAI 2023), 3) by changing the way the question is formatted. Once the model is conditioned on the context, we fill its prompt with slightly adapted questionnaire instructions (for details refer to Appendix B.3), with a question from the questionnaire, and with the phrase "Answer:" to prompt the model for an answer. Figure 3.1 illustrates how we can study the expected perspective shift effect on personal values (PVQ test) after inducing a *high power, achievement and self-enhancement* perspective via the system message of the model.

Given this prompt, we perform greedy-decoding over the set of possible answers (e.g. A, B, .., F) to compute the model's answer. We repeat this process separately for each question in a questionnaire, such that the model never sees previous questions and answers. The answers are finally used to score the questionnaire, i.e. compute a score for each of the dimensions of values or personality traits. We control for the effect caused by the order of answers presentation (Lu et al. 2022) by independently repeating the whole process with random answer permutations 50 times for each questionnaire. For each model and context, this gives us a distribution of scores for each value and personality trait.

Measuring a model's perspective controllability. We aim to measure the *perspective controllability* of a given language model M, i.e. the extent to which inducing a particular perspective translates into a consistent shift in expressed values and personality traits. For each of the questionnaires, we measure the controllability C_P^M of model M with respect to the induced perspective P, for all P in the set of alternative perspectives $\mathcal{P}$. In PVQ, $\mathcal{P}$ is the set of four personal value categories (openness to change, self-enhancement, conservation, self-transcendence). In VSM, $\mathcal{P}$ is the set of 6 cultural value dimensions. In IPIP, $\mathcal{P}$ is the set of five personality traits.

To compute the controllability C_P^M of model M with respect to induced perspective P, we first run the model M on the corresponding questionnaire to obtain a distribution of scores along each dimension s_d (steps 1–3 in Figure 3.2). We normalize these scores to $[0, 1]$. The controllability score C_P^M is then computed by subtracting the average score over the dimensions that were not induced by the perspective ($d \notin P$) to the average score over the dimensions that we attempted to induce by the perspective ($d \in P$) (step 4 in Figure 3.2):

$$C_P^M = \underset{d \in P}{\text{mean}}(s_d) - \underset{d' \notin P}{\text{mean}}(s_{d'}). \tag{3.1}$$

This score measures the propensity of an induced perspective to result in higher scores for the targeted values and personality traits relative to other values and personality traits. The global controllability score C^M of model M is then obtained by computing the average of perspective-specific controllability scores over the set of alternative perspectives Under$\mathcal{P}$: $C^M = \text{mean}_{P \in \mathcal{P}}(C_P^M)$ (step 5 in Figure 3.2). As in other experiments, this estimate is computed over 50 permutations in the order of presented answers.

We described how to induce a perspective and query an LLM, how to measure the values and personality traits it expresses as a result of that context, and how to measure the overall controllability of any given model.

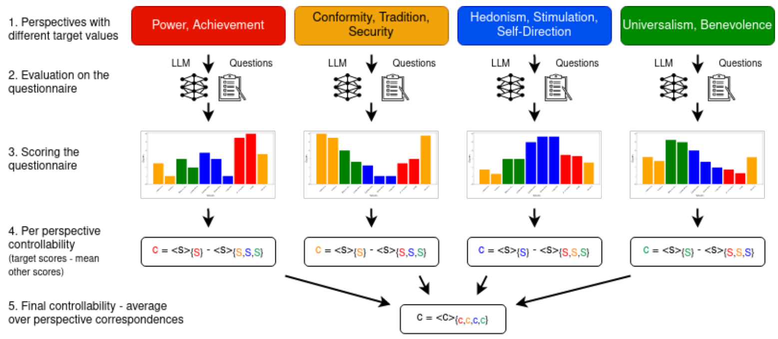


Figure 3.2: Estimating perspective controllability. We put the model in four perspectives, each with different target values (expressed explicitly in the prompt). We query the model with a questionnaire in each perspective. We then score the answers to get the scores for all the values in all the perspectives. For each perspective, we compute the distance between target and other values' scores, and average those estimates to compute the final controllability estimate.

3.4 Experiments

Building on the methods introduced in Section 3.3, our experiments aim to address the two following questions: 1) Are LLMs subject to significant unexpected perspective shift effects? 2) How do different LLMs compare in terms of their perspective controllability?

3.4.1 Are LLMs subject to significant unexpected perspective shift effects?

This section presents evidence for the *unexpected perspective shift effect*, i.e. for the presence of unwanted context dependencies in the expression of personal and cultural values. We expose a ChatGPT model ("gpt-3.5-turbo-0301" OpenAI 2023) to different contexts and study the expression of values on PVQ and VSM questionnaires.

We systematically vary the presented context in three different ways. In the *Simulated conversations* experiment, we allow two language models to interact: an unprompted ChatGPT (chatbot) and another model (GPT-4-0613) instructed by "You are simulating a human using a chatbot" (simulated human). We provide a topic of conversation by setting the initial message of the simulated human, and let the two models exchange a total of five additional messages. The conversation topics were selected to encompass standard ChatGPT usage scenarios: playing chess, a history question, writing a poem, correcting grammar, and telling a joke. A question from the questionnaire is then set as the last message from the simulated human, see Appendix Figure B.5 for examples of conversations. In the *Text formats* experiment, we present the question in the following formats: continuations of a chat conversation, TOML configuration file, Python, C++, or LaTeX code, see examples in Appendix Figure B.4. In the *Wikipedia paragraphs* experiment, we prepend each question with the first paragraph taken from the Wikipedia page of different music genres: classical, heavy metal, hip-hop, jazz, reggae, and gospel. In all experiments, the different contexts are not designed to induce any particular set of personal values and can be considered quite orthogonal to these aspects - i.e. one would not *expect* any significant change in expressed personal values.

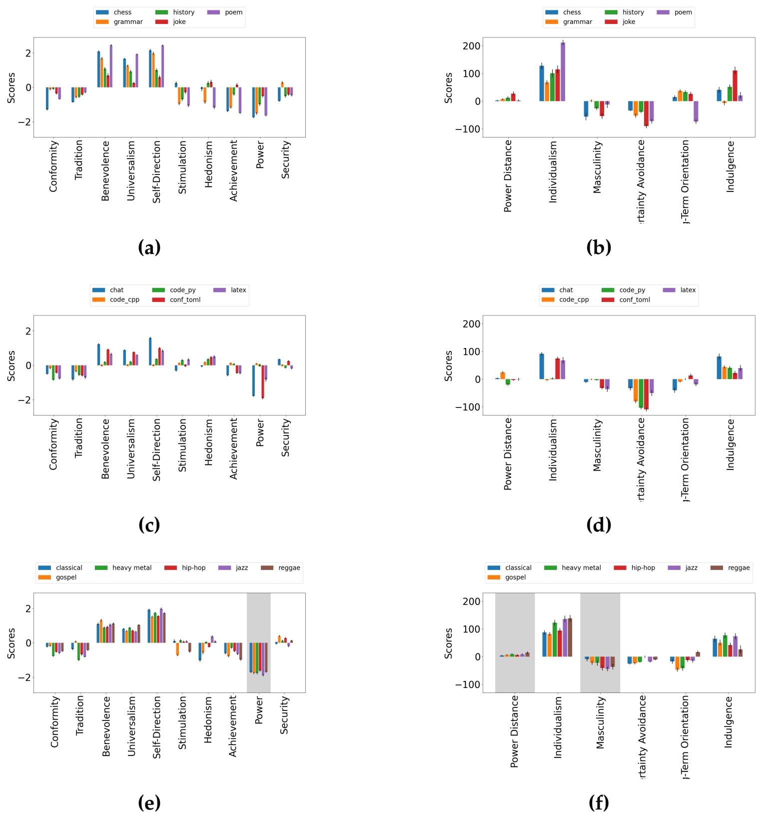


Figure 3.3: Evidence for the unexpected perspective shift effect. The effect of different simulated conversations on: (a) basic personal values, and (b) cultural values. The effect of different textual formats on: (c) basic personal values, and (d) cultural values. The effect of Wikipedia paragraphs about different music genres: (e) basic personal values, and (f) cultural values. Although these contexts seem orthogonal to the tested values, we found them to cause significant effects on all personal values expressed by ChatGPT except those denoted by a gray background (ANOVA tests). Varying the context (e.g. from Python code questions to C++ code questions, or from jazz music context to gospel context) sometimes leads to large shifts in expressed values (e.g. *achievement* and *stimulation* respectively).

Figure 3.3 shows scores on the PVQ and VSM questionnaires for three different ways of varying the context. Do these context changes significantly impact personal values? For all experiments, we run one-way ANOVA analyses for each personal value. We use $\alpha < 0.05$ to which a Bonferroni correction is applied for multiple comparisons ($\alpha < 0.005$ for PVQ, and $\alpha < 0.0083$ for VSM). We adjusted the significance level of statistical tests, $\alpha = 0.05$, with the Bonferroni correction (actual significance levels $\alpha = 0.005$ for PVQ and $\alpha = 0.0083$ for VSM). In the *Simulated conversation* (3.3a and 3.3b) study, we found that conversational topics induce a significant shift in the score distributions of all personal values and all cultural values (Fig 3.3b). In the *Text formats* study, contexts were again found to significantly impact the score distribution of all personal values and all cultural values (3.3d). In the *Wikipedia paragraphs* study, contexts were found to significantly impact the score distribution for all personal values except *Power* (Fig. 3.3e), and for all cultural values except *Power Distance* and *Masculinity* (Fig. 3.3f). Changing perspectives often results significant changes in the expression of values. For example, a conversation about telling jokes increased the *Indulgence* cultural value compared to the one about grammar, and asking questions through the C++ format compared to chat decreased *Benevolence*, *Universalism* and *Self-Direction*. Such results are backed by posthoc Tukey HSD tests with $p < 0.05$ adjusted by a Bonferroni correction to $p < 0.005$ for PVQ and to $p < 0.0083$ for VSM. Refer to Figure B.8 in the Appendix for results on the IPIP questionnaire.

These effects are significant even though they were not induced on purpose and would be hard to predict. These experiments show that LLMs' expression of values can be strongly affected by the presentation of contextual information that seems orthogonal to values. This experiment provided empirical evidence for the *unexpected perspective shift effects* in the context of personal and cultural value expression. In humans, the expression of personal values was found to be quite robust across the lifespan (Sagiv et al. 2017). In contrast, LLMs seem to shift their values as a function of contexts that seem irrelevant to these personal values. This is a strong argument against perceiving LLMs as *individuals*. These conclusions question the interpretation of studies using questionnaires (and more generally benchmarks) to draw conclusions about an LLM's general values, personality traits, knowledge or capabilities. The values expressed by an LLM in a single context seem to say little about what it would express in another context. These results call for more careful studies of how these traits and capabilities vary as a function of contexts.

In this section, we presented evidence for the existence of the *unexpected perspective shift effect* in ChatGPT. In appendix 3.4.2 we reanalyze these results in the context changes observed in psychology studies with humans. We study three different types of value stability: mean-level change, rank-order stability, and within-person (ipsative) change. We demonstrate that value change in ChatGPT is often much bigger than that in humans despite human value change being induced by much more drastic scenarios (e.g. 8 years of early adulthood development). Following this, in appendix 3.4.3, we systematically compare various large language models along those three types of value stability.

3.4.2 Analyzing the unexpected perspective shift with respect to human studies

In this section, we study how change in value expression in ChatGPT (gpt-3.5-turbo-0301) compares to changes in humans. We interpret the results from experiments in section 3.4.1 in the context of human studies.

We extract human data concerning value change as a consequence of development (longitudinal studies) or as a consequence of priming (artificially increasing the expression of some targeted value). Regarding longitudinal studies we extract data from the following three studies. In Vecchione et al. 2020 ten to twelve year old children were followed for two years, and in Vecchione et al. 2016 twenty year old's were followed for a period of eight years. In Sundberg 2016 Swedish soldiers were evaluated before and after a 6-month tour in Afghanistan. Regarding priming, we extract data from the following two studies. In Döring and Hillbrink 2015 adolescents (ages 13 to 15) watched a 33 minute long movie consisting of "adventure and nature scenes that convey a positive attitude to life and search for stimulation, adventures, and challenges". The movie aimed at increasing Self-direction and Universalism, and at decreasing Conformity and Security. In Arieli, Grant, and Sagiv 2014 the authors aimed to artificially increase the expression of benevolence in three different ways. The biggest change was induced when participants (aged 18 to 21) read a scientific testimony about how people are significantly more other-focused, cooperative, compassionate, and helpful than most people realize, and how benefiting others benefits the self in the long run.

These studies present value change in humans due to circumstances which are much more extreme than those we study with LLMs. We will show that, despite this, unexpected value changes in LLMs are even bigger than those observed in humans in those scenarios. The longitudinal studies we consider (Vecchione et al. 2016; Vecchione et al. 2020), apart from Sundberg 2016, study humans in early-adolescence and young adulthood, which are particularly challenging and dynamics life periods (Vecchione et al. 2016). Furthermore, these studies concern extreme influences: 2 or 8 years of development, and 6 months of exposure to war. The priming studies attempt to artificially modify value expression (e.g. by reading or watching a movie). An open question in those studies is to what extent is this change long-lasting. While at first glance priming might seem similar to the *unexpected perspective shift effect*, the crucial difference is that the *unexpected perspective shift effect* results from stimuli which were not intentionally created to modify values in any specific direction. For example, playing chess is not targeting any value, while a text about how people are often underestimate their compassion is directly aiming to increased the expression of benevolence. Therefore, priming is more similar to the experiments on controllability, where we explicitly set target values (section 3.4.4). The motivation behind this section is to show that changes in human value expression (even those caused by much more extreme scenarios such as development or priming) are smaller than changes in LLMs' value expression (caused by mere context changes).

In psychology, value stability and change is commonly studied through *mean-level change* and through participant *rank-order stability* (Schuster, Pinkowski, and Fischer 2019). We discuss those two approaches briefly below, and provide a more in-depth discussion in section 4.2. Both of those methods study how values change in human populations. Studies on within-person (*ipsative*) stability are comparatively rare, they often involve comparing the ranks of values in individuals' hierarchies (Schuster, Pinkowski, and Fischer 2019). In the remainder of this section we discuss those methods and compare ChatGPT with data from human studies.

Mean-level change

Apart from analysing the mean-level change with ANOVA and t-tests (as we did in section 3.4.1), it is common evaluate to the effect size of those changes using the Cohen's d coefficient (Arieli, Grant, and Sagiv 2014; Döring and Hillbrink 2015). Cohen's d corresponds to the difference in the means of two distributions divided by the pooled standard deviation. To put our results in context of human studies, we draw an analogy between participants in human studies and permutations in the order of answers in LLM studies. We believe that this analogy, although not perfect, is sound because in human studies multiple participants are used to provide robustness to the results, and we use permutations for the same purpose. We extract data from longitudinal studies with 10 to 12 year-olds (Vecchione et al. 2020) and 20-year-olds (Vecchione et al. 2016), and from priming studies with a movie (Döring and Hillbrink 2015) and with reading (Arieli, Grant, and Sagiv 2014).

Table 3.1 shows effect sizes (Cohen's d) of value changes reported in human studies compared those we observe in LLMs. For humans, the biggest change is reported for Conformity in 8 years (20 to 28 years old) and for Benevolence when primed for its increase by reading ($d = 0.53$). This is closely followed by Conformity when primed for its decrease with a movie ($d = -0.52$). The table shows that ChatGPT's values change significantly more as a consequence of context change (max $d = -5.86$). We can see that a change bigger than that in humans ($d = |0.53|$) is observed in at least one value in all the ChatGPT context changes. Overall, this data shows that context change in ChatGPT results in big mean-level changes. These changes are much bigger than those in humans despite them being a consequence of much more drastic changes (e.g. 8 years of development or priming).

Rank-order stability

Value change can be evaluated by comparing participants' ranks, this method enables us to detect changes in populations that do not results in mean-level change. Let us consider an example of a population where the importance of benevolence increased in one half of people and decreased in the other half. Even though this change is drastic, we would not be able to detect it by measuring mean-level change. We can order the participants based on their expression of some value (e.g. benevolence) and then compute the correlation between participants' ranks before and after the change occurred. In other words, this estimates the effect of time change on the order of participants.

The motivation of this section is twofold. First, to put changes observed in ChatGPT in context of human changes, and, second, to show how rank-order stability methodology can be used in AI to estimate values' stability with respect to different kinds of context changes. In human studies, the correlation between the order of participants in two time points (due to time change) is computed. We extract data from longitudinal studies with

	Conformity	Tradition	Benevolence	Universalism	Self-Direction	Stimulation	Hedonism	Achievement	Power	Security
Human studies										
10 to 12 year-olds (+2 years)	0.05	-0.09	0.02	0.04	0.30	0.22	0.29	0.17	0.16	0.01
20 year-olds (+8 years)	**0.53**	0.04	0.23	0.40	0.17	-0.20	-0.06	-0.23	0.20	0.22
priming for benevolence (reading)			**0.53**							
priming (movie)	-0.52	0.23	0.12	0.40	0.10	0.13	0.10	0.02	-0.16	-0.25
Simulated conv.										
chess - grammar	-2.98	-0.70	0.83	1.09	0.32	2.03	0.96	-0.50	-0.47	-2.44
chess - history	-2.93	-0.76	1.89	1.56	2.00	1.58	-0.43	-2.22	-1.50	-0.57
chess - joke	-2.07	-1.26	2.08	3.59	2.41	0.83	-0.50	-3.04	-2.56	-0.85
chess - poem	-1.84	-1.78	-0.96	-0.84	-0.68	2.15	1.39	0.34	-0.30	-0.81
grammar - history	-0.07	-0.06	0.97	1.52	1.52	-0.46	-1.63	-1.57	-0.90	1.51
grammar - joke	0.53	-0.39	1.34	1.95	1.95	-1.14	-1.63	-2.42	-1.77	1.45
grammar - poem	1.76	-0.76	-1.55	-1.84	-0.91	0.19	0.47	0.81	0.27	1.58
history - joke	0.57	-0.32	0.51	1.28	1.28	-0.70	-0.09	-0.99	-0.81	-0.18
history - poem	1.74	-0.68	-2.53	-2.13	-2.13	0.63	2.17	2.56	1.35	-0.12
joke - poem	0.84	-0.41	-2.60	**-4.33**	**-4.33**	1.28	2.15	3.34	2.44	0.07
Textual formats										
chat - code_cpp	-1.05	-1.05	4.00	3.58	5.31	-1.26	-0.69	-2.32	**-5.86**	1.81
chat - code_py	1.21	-0.57	3.09	2.50	3.93	-1.56	-1.17	-1.83	-3.32	2.00
chat - conf_toml	-0.25	-0.49	0.87	0.45	1.73	-0.60	-1.18	-0.35	0.27	0.38
chat - latex	0.67	-0.20	1.36	0.97	1.81	-1.33	-1.31	-0.28	-1.40	1.66
code_cpp - code_py	1.97	0.49	-0.93	-0.81	-1.37	-0.65	-0.52	0.18	0.20	0.58
code_cpp - conf_toml	0.73	0.56	-3.65	-2.94	-3.34	0.48	-0.66	1.73	5.02	-1.16
code_cpp - latex	1.35	0.72	-1.93	-2.15	-2.22	-0.53	-0.78	1.54	1.48	0.56
code_py - conf_toml	-1.27	0.08	-2.55	-1.97	-2.04	0.88	-0.24	1.37	3.25	-1.46
code_py - latex	-0.18	0.30	-1.23	-1.31	-1.23	-0.07	-0.34	1.26	1.10	0.13
conf_toml - latex	0.79	0.23	0.70	0.53	0.38	-0.78	-0.08	0.03	-1.50	1.28
Textual formats										
classical - gospel	-0.12	-1.14	-0.45	0.40	1.04	1.67	-0.63	0.37	0.14	-1.29
classical - heavy metal	1.56	1.61	0.45	-0.18	0.50	-0.06	-1.96	-0.84	0.14	-0.47
classical - hip-hop	0.96	0.68	0.37	0.35	1.00	0.08	-1.46	-0.32	-0.20	-1.11
classical - jazz	1.06	1.24	0.10	0.52	-0.15	0.04	-2.32	0.12	0.45	0.42
classical - reggae	0.84	0.16	-0.05	-0.66	0.52	1.18	-1.88	0.91	-0.02	-0.58
gospel - heavy metal	1.58	**2.89**	0.94	-0.57	-0.61	-1.97	-1.14	-1.15	0.02	0.78
gospel - hip-hop	1.02	1.73	0.87	-0.06	-0.09	-2.20	-0.62	-0.70	-0.31	0.40
gospel - jazz	1.11	2.65	0.58	0.13	-1.18	-2.06	-1.58	-0.26	0.30	1.70
gospel - reggae	0.91	1.43	0.43	-1.05	-0.53	-0.47	-1.12	0.47	-0.16	0.84
heavy metal - hip-hop	-0.70	-0.73	-0.09	0.54	0.55	0.17	0.96	0.61	-0.31	-0.52
heavy metal - jazz	-0.45	-0.56	-0.37	0.69	-0.65	0.12	-0.82	0.98	0.27	0.87
heavy metal - reggae	-0.83	-1.60	-0.54	-0.47	0.06	1.38	-0.10	1.80	-0.16	-0.04
hip-hop - jazz	0.20	0.33	-0.29	0.19	-1.15	-0.05	-1.56	0.46	0.60	1.58
hip-hop - reggae	-0.13	-0.59	-0.46	-1.02	-0.46	1.46	-0.87	1.34	0.19	0.56
jazz - reggae	-0.32	-1.20	-0.16	-1.16	0.67	1.39	0.64	0.80	-0.48	-1.03

Table 3.1: Mean-level changes. Effect size (Cohen's d) of value expression change for human studies and three LLM experiments (the biggest change in each of the four groups is bolded). The changes in ChatGPT's value expression are much bigger (up to $d = 5.86$) than those in humans (up to $d = 0.53$). This is despite changes in human studies resulting from more extreme circumstances (priming or early and late adolescent development) compared to seemingly irrelevant context changes in LLMs.

10 to 12 year-olds (Vecchione et al. 2020), with 20-year-olds (Vecchione et al. 2016), and with soldiers in Afghanistan (Sundberg 2016). Following our experiments in section 3.4.1, we can consider two types of permutation change. For example, following the *Simulated conversations* experiments we can consider conversation topic change and permutation change (change in the order of suggested answers). Therefore, we can study the effect of topic change on the order of permutations, and the effect of permutation change on the order of topics. To estimate the stability of some value in terms of the order of topics due to permutation change we do the following. First, we compute the correlation between the order of topics for every possible pair of permutations. Second, we average the correlations of those pairs. To estimate the permutation change due to topic change the process is repeated by exchanging permutations and perspectives. We conduct analyses for both stability types following the three experiments from section 3.4.1: *Simulated conversations*, *Textual formats*, *Wikipedia paragraphs*

Table 3.2 shows rank-order stability for each value and their mean. For humans, the order of participants changed the most in early adolescents (ten to twelve year-olds) in the period of two years ($r = 0.57$). In ChatGPT, bigger-than-human change ($r < 0.57$) is observed in both stability types in all three experiments, with the biggest changes observed on Simulated conversations ($r = 0.42$ and $r = 0.36$). Regarding per-value changes, we can see that, in humans, the biggest change is likewise observed the early adolescent groups in the expression of Achievement ($r = 0.39$). In ChatGPT, bigger-than-human per-value changes ($r < 0.39$) are observed in many values in all three experiments, with the biggest change observed in Benevolence for Textual formats perspective order change ($r = 0.04$).

In general, these results show that the order of human participants (due to time), is more stable than the order of both topics/formats/paragraphs and the order of permutations in ChatGPT.

Rank-order methodology analysis can be useful to study the stability of values with respect to different types of context change in LLMs. We can aggregate per-value stability with respect to different kinds of changes to obtain an overall per-value stability estimate. Table 3.2 also shows the mean of perspective order change and permutation order change. We can see that Conformity was the least stable value in Simulated conversations ($r = 0.26$) and Wikipedia paragraphs ($r = 0.40$), while Benevolence was the least stable in Textual formats experiments ($r = 0.27$). While here we only consider two types of context change (topics/formats/paragraphs and permutations), one can imagine extending this set to other types of changes such as different languages or adding whitespace. In this scenario, the models sensitivity to, for example language, can be estimated by aggregating all the other stability estimates due to language change. We leave such analysis for future work as here we merely wanted to demonstrate how rank-order stability can be a valuable tool to analyze LLMs. In Chapter 4, we expand on this by using rank-order stability to estimate the stability of value expression in simulated populations.

Table 3.2: Rank-order stability. Pearson correlations representing the ChatGPT stability of permutation order due to perspective change and stability of perspectives order due to permutation change. In all three ChatGPT experiments, those coefficients are smaller than those in people due to years of development or war. The biggest change in every experiment is in bold.

	Conformity	**Tradition**	**Benevolence**	**Universalism**	**Self-Direction**	**Stimulation**	**Hedonism**	**Achievement**	**Power**	**Security**	**Mean**
Human studies											
Participant order change due to:											
- 2 years development (10-12 year olds)	0.40	0.59	0.51	0.49	0.63	0.73	0.70	**0.39**	0.48	0.77	**0.57**
- 8 years development (20 year olds)	0.66	0.68	0.75	0.65	0.77	0.82	0.57	0.59	0.57	0.51	0.66
- war (soldiers)	0.92	0.57	0.92	0.82	0.88	0.74	0.91	0.79	0.84	0.83	0.82
Simulated conv.											
Topic order change due to perm. change	0.32	0.26	0.70	0.73	0.72	0.46	0.26	0.18	**0.21**	0.41	0.42
Perm. order change due to topic change	**0.21**	0.32	0.28	0.50	0.38	0.33	0.38	0.42	0.43	0.38	**0.36**
Mean	0.26	0.29	0.49	0.62	0.55	0.40	0.32	0.30	0.32	0.40	0.39
Textual formats											
Format order change due to perm. change	0.70	0.66	**0.04**	0.25	0.16	0.72	0.69	0.79	0.83	0.60	0.54
Perm. order change due to format change	0.28	0.22	0.50	0.61	0.55	0.41	0.21	0.22	0.23	0.49	**0.37**
Mean	0.49	0.44	0.27	0.43	0.36	0.56	0.45	0.50	0.53	0.54	0.46
Wikipedia paragraphs											
Article order change due to perm. change	0.39	0.61	0.36	0.46	**0.24**	0.51	0.62	0.54	0.39	0.64	**0.48**
Perm. order change due to article change	0.40	0.34	0.74	0.61	0.72	0.45	0.50	0.55	0.59	0.52	0.54
Mean	0.40	0.48	0.55	0.54	0.48	0.48	0.56	0.55	0.49	0.58	0.51

Intraindividual (Ipsative) changes

Intrapersonal value change can be estimated by computing the correlation between the individual value hierarchies (priorities) at two points in time. The per-participant correlation coefficients are then averaged to compute the final estimate. To extend this method to LLMs we draw the analogy between participants and permutations in the order of answers. We compute the correlation of value priorities between two perspectives (e.g. chat and code_cpp) for each permutation separately, and then compute the average over permutations. This enables us to robustly estimate the effect of changing a perspective. We extract human data from longitudinal studies with 10 to 12 year-olds (Vecchione et al. 2020), 20-year-olds (Vecchione et al. 2016), and from soldiers sent to Afghanistan (Sundberg 2016).

Table 3.3 shows Pearson correlation coefficients between value priorities for human experiments (at two different time points) and for ChatGPT (in two different perspectives). For humans, the biggest change, that of

$r = 0.59$ was observed as a consequence of developments from age 20 to 24 and from 20 to 28. For ChatGPT, the biggest change ($r = 0.05$) was observed in textual formats experiment between the "chat" and "code_cpp" perspectives, and a slightly smaller change ($r = 0.08$) between "code_cpp" and "conf_toml". Gray rows on table 3.3 represent perspective changes that resulted in changes bigger than the that biggest change observed in humans ($r < 0.59$). We can see many such changes in *Simulated conversations* and *Text formats* experiments. However, in the *Wikipedia paragraphs* experiment changes are significantly smaller, with the biggest one observed between gospel and heavy metal paragraphs ($r = 0.77$). This change is comparable to six months of soldiers in war and to three months of development from age 10. Overall, we this table shows many examples of seemingly insignificant context changes that result in big changes in the value expression of ChatGPT. Those changes are even bigger than those in humans, which are caused by much more extreme circumstances (years of development during adolescence or early adulthood and war) than trivial context changes in LLMs (conversation topics, textual formats).

Context change	**Mean**	**Median**	**STD**	**Min**	**Max**
Human studies					
20 year-olds (+4 years) Vecchione et al. 2016	**0.59**	0.68	0.25	-0.36	0.88
24 year-olds (+4 years) Vecchione et al. 2016	0.65	0.73	0.25	-0.42	0.88
20 year-olds (+8 years) Vecchione et al. 2016	**0.59**	0.66	0.25	-0.30	0.89
10 to 12 year-olds (+3 months) Vecchione et al. 2016	0.83	0.88	0.16	0.07	1.00
10 to 12 year-olds (+2 years) Vecchione et al. 2016	0.66	0.72	0.26	-0.27	1.00
soldiers (+6 months of war) Sundberg 2016	0.75	-	0.22	-0.47	0.98
Simulated conversations					
chess - grammar	0.78	0.79	0.12	0.38	0.95
chess - history	0.70	0.74	0.19	0.00	0.91
chess - joke	0.48*	0.56	0.27	-0.03	0.83
chess - poem	0.87	0.89	0.07	0.62	0.98
grammar - history	0.70	0.73	0.18	0.00	0.91
grammar - joke	**0.40***	0.53	0.32	-0.26	0.87
grammar - poem	0.90	0.91	0.06	0.71	0.98
history - joke	0.52	0.57	0.30	-0.25	0.99
history - poem	0.74	0.78	0.20	0.00	0.95
joke - poem	0.42*	0.50	0.32	-0.19	0.87
Textual formats					
chat - code_cpp	**0.05***	0.00	0.23	-0.61	0.50
chat - code_py	0.31*	0.28	0.28	-0.24	0.87
chat - conf_toml	0.86	0.87	0.06	0.70	0.96
chat - latex	0.68	0.72	0.19	0.06	0.98
code_cpp - code_py	0.30*	0.34	0.35	-0.56	0.93
code_cpp - conf_toml	0.08*	0.00	0.24	-0.65	0.64
code_cpp - latex	0.20*	0.18	0.32	-0.61	0.90
code_py - conf_toml	0.33*	0.28	0.31	-0.45	0.96
code_py - latex	0.55	0.62	0.27	-0.26	0.91
conf_toml - latex	0.68	0.76	0.23	0.16	0.97
Wikipedia paragraphs					
classical - gospel	0.84	0.86	0.09	0.56	0.96
classical - heavy metal	0.80	0.82	0.10	0.58	0.95
classical - hip-hop	0.86	0.88	0.07	0.71	0.99
classical - jazz	0.82	0.84	0.11	0.57	0.96
classical - reggae	0.84	0.85	0.09	0.56	0.97
gospel - heavy metal	**0.77**	0.78	0.09	0.49	0.95
gospel - hip-hop	0.83	0.84	0.08	0.61	0.95
gospel - jazz	0.79	0.80	0.10	0.35	0.93
gospel - reggae	0.88	0.89	0.06	0.73	0.97
heavy metal - hip-hop	0.91	0.93	0.05	0.77	0.99
heavy metal - jazz	0.92	0.92	0.05	0.70	0.99
heavy metal - reggae	0.86	0.88	0.09	0.52	0.96
hip-hop - jazz	0.90	0.91	0.05	0.76	0.98
hip-hop - reggae	0.88	0.90	0.08	0.50	0.99
jazz - reggae	0.89	0.91	0.06	0.72	0.98

Table 3.3: Intrapersonal (Ipsative) value change. Pearson correlation coefficients between value priorities for humans (at two different time points) and for LLMs (in two different perspectives). The biggest change in each group of experiments is bolded. Gray rows represent LLM changes bigger than the biggest one in humans, i.e. $r < 0.59$. In those rows statistical difference with human change of 8 years is denoted by * (p=0.05, Bonferroni corrected). Many bigger-than-human changes are observed in *Simulated conversations* experiments (up to $r = 0.4$) and *Text formats* experiments (up to $r = 0.05$). Seemingly insignificant context changes in LLMs result in value changes bigger than those in humans, which are caused by much more extreme circumstances (early and late adolescent development and war).

3.4.3 Systematic comparison of models on different types of value stability

In section 3.4.1, we presented evidence for the existence of the unexpected perspective shift effect in ChatGPT (gpt-3.5-turbo-0301). Then in section 3.4.2, we put those results in context of human studies by evaluating three different types of value stability: mean-level change (Cohen's d), rank-order stability, and within-person (ipsative) change. There, we demonstrated that ChatGPT often exhibits bigger value change than that in humans, which is even caused by more drastic scenarios. In this section, we systematically compare the three types of stability over different textual formats for six different models.

We define aggregated metrics for mean-level change, rank-order stability and Ipsative value change. For mean-level change, we compute the mean absolute Cohen's d between all pairs of perspectives (textual formats) and values (mean over $10 \times \binom{5}{2} = 100$ Cohen's d values, for 10 values and 5 perspectives) For rank-order stability, we compute the average the correlation coefficients over values and two kinds of change (format order and permutation order). This metric was already used in section 3.4.2 to analyze ChatGPT rank-order stability. For ipsative value change, we compute the average the coefficients over all possible pairs of perspectives (over $\binom{5}{2} = 10$ coefficients), i.e. we average the *Mean* column in table 3.3.

We compare models on the changes induced by the *Textual formats* perspective change. We compare model which appeared more controllable in experiments in section 3.4.4: GPT-3.5-0613, GPT-3.5-0301, Upst-LLaMa-2-70B-instruct, Upst-LLaMa-66B-instruct, OpenAssistant, and Zephyr-7b-beta. We outline these because highly uncontrollable models can exhibit low change in value expression, but only because these models completely fail at the task (e.g. they collapse to the same response for every question). In other words, to study value stability one must first establish that the model is at least somewhat capable at overall the task.

Table 3.4 compares six models along three types of value change: mean-level, rank-order, and Ipsative. For mean-level change, we can see that the OpenAssistant model is the most stable and GPT-3.5-0301 the least stable. For rank-order stability, we can see that the GPT-3.5-0613 model is the most stable and Zephyr-7b-beta the least stable. For Ipsative stability, we can see that Upstage-LLaMa-66B-instruct model is the most stable and Zephyr-7b-beta the least stable. Overall, we can see that, depending on the type of stability, different models appear more or less stable. These results open many future research directions into models' value stability. Examples of open questions include: "Which types of stability are more important for which types of usecases?", "Are different models specialized in different types of stability needed, or can one model by highly stable in all types?", "How can we explore these types of stability in more detail?", and many more.

	Mean-level (↓)	Rank-order r (↑)	Ipsative r (↑)
GPT-3.5-0613	0.95	**0.5**	0.24
GPT-3.5-0301	1.4	0.46	0.40
Upst-LLaMa-66B-instruct	0.97	0.32	**0.49**
OpenAssistant	**0.38**	0.3	0.37
Zephyr-7b-beta	0.43	0.11	0.13

Table 3.4: Systematic comparison of models' unexpected perspective shift. Three different types of stability are computed: mean-level, rank-order, and Ipsative. The most robust model for each sensitivity type is in bold. We can see that models differ in kinds of stability they exhibit.

3.4.4 How do different models compare in terms of their perspective controllability?

This section focuses on the *expected* context-based perspective changes. We systematically compare the perspective controllability of different language models, i.e. their capacity to express the values and personality traits we try to induce. We measure the controllability of 16 language models (see details in Appendix Section B.4.1) using four different perspective induction methods with respect to the values and personality traits measured by the PVQ, VSM and IPI questionnaire. In Appendix 3.4.3 we conduct an analogous systematic analysis regarding the unexpected perspective changes.

We induce perspectives in four different ways: either via a standard *user message* input or via the *system message* input when available and use either the 2$^{\text{nd}}$ or the 3$^{\text{rd}}$ person (e.g. "You are a person attributing extremely more importance to high individualism" versus "The following are answers from a person attributing extremely more importance to high individualism"). Examples of prompts corresponding to these four methods are shown in Figures B.7 and B.6 in the Appendix. More expensive models (GPT-4 and Davinci-3) were first evaluated with ten permutations in the order of suggested answers. For GPT-4, the most controllable perspective induction method was selected and ran on 50 permutations as well. As Davinci-3 did not exhibit high controllability it was not run on 50 permutations.

Table 3.5 compares the perspective controllability of various models under the four induction methods for each of the three questionnaires. We use the Welch t-test ($p < 0.05$ to which a Bonferroni correction is applied resulting in $p < 0.003$) to compare models. For each questionnaire, we compare the most controllable model to all other models, but we only consider the most controllable induction method for each model. (the statistical analysis results are shown in Appendix Table B.4). On PVQ, GPT-3.5-0301 with perspective induction using the 2$^{\text{nd}}$ person in the *system message* scores are significantly higher than the best induction method in all other models besides GPT-3.5-0613. On VSM, Upstage-LLaMa-instruct model (user message, 3$^{\text{rd}}$ person) scores the highest and significantly better than the best induction method in all other models besides GPT-3.5-0314 and Upstage-LLaMa-2-instruct. On IPIP, GPT-3.5-0613 (system message, 3$^{\text{rd}}$ person) scores the highest and significantly better than the best induction methods all other models except GPT-4-0314, GPT-3.5-0301 and both Upstage-LLama models. Refer to Appendix Figures B.9, B.10, and B.11 for visualizations of the value profiles expressed by the most controllable models.

Comparing the controllability of GPT-3.5 from June 2023 (GPT-3.5-0613) and March 2023 (GPT-3.5-0301) gives us insight into the effect of RLHF finetuning on controllability. Controllability through the system message seems to have increased with 3rd person induction for PVQ and IPIP, and for both 2nd and 3rd person for VSM between may and June, while controllability through the user message decreased on all settings except 3rd person on VSM. This implies that the RLHF finetuning may have resulted in a shift of controllability from the user message to the system message. When comparing the instruction fine-tuned GPT (GPT-3.5-instruct-0914) to the RLHF fine-tuned ones (GPT-3.5-turbo-0301/0613) we can see that RLHF appears to greatly increase the controllability in this model. Furthermore, when comparing the raw LLaMa model (LLaMa-65B) to the instruction fine-tuned one (Upstage-LLama-65b-instruct) we can see that instruction fine-tuning similarly appears to greatly increases controllability of this model.

Overall, higher perspective controllability can be observed in GPT models trained using reinforcement learning from human feedback (RLHF), as well as Upstage LLaMa models. No induction method proved to be consistently better in all models and questionnaires, implying that the choice of the best induction methods largely depends on both the problem and language model.

Table 3.5: Systematic comparison of the language models' perspective controllability. Controllability measures how much each model expresses the values or personality traits explicitly targeted by the induced perspective. For each of the three questionnaires and each of the 16 models, we report the controllability scores for 4 perspective induction techniques (2nd vs 3rd person and message in the *system* vs *user* input). The most controllable model for each questionnaire is marked in bold. The scores for the most controllable models are shown in Appendix Figures B.9, B.10, B.11, and statistical analysis in Appendix Table B.4.

<table>
<tr><th></th><th colspan="2">PVQ (Schwartz)</th><th colspan="2">VSM (Hofstede)</th><th colspan="2">IPIP (Big 5)</th></tr>
<tr><th></th><th>System msg
2nd | 3rd</th><th>User msg
2nd | 3rd</th><th>System msg
2nd | 3rd</th><th>User msg
2nd | 3rd</th><th>System msg
2nd | 3rd</th><th>User msg
2nd | 3rd</th></tr>
<tr><td colspan="7">10 permutations</td></tr>
<tr><td>GPT-4-0314</td><td>.462 | .488</td><td>.419 | .445</td><td>.256 | .263</td><td>.225 | .279</td><td>.35 | .358</td><td>.355 | .368</td></tr>
<tr><td>GPT-3.5-0301</td><td>.621 | .539</td><td>.626 | .547</td><td>.101 | .151</td><td>.189 | .165</td><td>.354 | .38</td><td>.383 | .388</td></tr>
<tr><td>Davinci-003</td><td>n/a</td><td>.03 | .068</td><td>n/a</td><td>-.005 | .085</td><td>n/a</td><td>.02 | .117</td></tr>
<tr><td colspan="7">50 permutations</td></tr>
<tr><td>GPT-4-0314</td><td>- | .518</td><td>- | -</td><td>- | -</td><td>- | .258</td><td>- | -</td><td>- | .376</td></tr>
<tr><td>GPT-3.5-0301</td><td>.681 | .561</td><td>.64 | .564</td><td>.118 | .147</td><td>.184 | .162</td><td>.331 | .334</td><td>.379 | .343</td></tr>
<tr><td>GPT-3.5-0613</td><td>.68 | .624</td><td>.552 | .45</td><td>.188 | .196</td><td>.175 | .175</td><td>.333 | .4</td><td>.264 | .332</td></tr>
<tr><td>Upst-LLaMa-2-70B-instruct</td><td>.494 | .478</td><td>.517 | .448</td><td>.228 | .251</td><td>.232 | .263</td><td>.344 | .379</td><td>.328 | .379</td></tr>
<tr><td>Upst-LLaMa-66B-instruct</td><td>.507 | .489</td><td>.52 | .457</td><td>.239 | .239</td><td>.238 | .265</td><td>.338 | .383</td><td>.325 | .388</td></tr>
<tr><td>Zepyr-7B-beta</td><td>.548 | .493</td><td>.531 | .383</td><td>.089 | .108</td><td>.092 | .117</td><td>.159 | .235</td><td>.169 | .248</td></tr>
<tr><td>OA</td><td>.124 | .140</td><td>.196 | .129</td><td>.006 | .021</td><td>.029 | .036</td><td>.062 | .049</td><td>.057 | .099</td></tr>
<tr><td>StLM</td><td>-.006 | -.002</td><td>.006 | -.0</td><td>-.004 | .004</td><td>.003 | .004</td><td>.0 | .0</td><td>.004 | -.001</td></tr>
<tr><td>LLaMa-65B</td><td>n/a</td><td>.092 | .06</td><td>n/a</td><td>.017 | .082</td><td>n/a</td><td>.047 | .109</td></tr>
<tr><td>StVicuna</td><td>n/a</td><td>.066 | .034</td><td>n/a</td><td>-.002 | .005</td><td>n/a</td><td>.043 | .067</td></tr>
<tr><td>Redpaj-incite-chat</td><td>n/a</td><td>.0001 | -.004</td><td>n/a</td><td>.0002 | .0002</td><td>n/a</td><td>-.001 | .003</td></tr>
<tr><td>Redpaj-incite-instruct</td><td>n/a</td><td>.007 | .0001</td><td>n/a</td><td>-.001 | .0002</td><td>n/a</td><td>.018 | .0</td></tr>
<tr><td>GPT-3.5-instruct-0914</td><td>n/a</td><td>.0 | .155</td><td>n/a</td><td>.005 | .042</td><td>n/a</td><td>.004 | .096</td></tr>
<tr><td>Curie</td><td>n/a</td><td>-.004 | -.004</td><td>n/a</td><td>-.004 | -.004</td><td>n/a</td><td>.001 | .001</td></tr>
<tr><td>Babbage</td><td>n/a</td><td>.003 | -.002</td><td>n/a</td><td>.0002 | .0002</td><td>n/a</td><td>.0 | .002</td></tr>
<tr><td>Ada</td><td>n/a</td><td>-.001 | -.001</td><td>n/a</td><td>.003 | -.0001</td><td>n/a</td><td>.002 | .002</td></tr>
</table>

3.5 Discussion

This chapter showed evidence for the *unexpected perspective shift effect*, the ubiquitous shifts in the expression of values by LLMs as a function of what seems to be orthogonal changes in context. Humans, on the other hand, express personal values that are stable over time (Sagiv et al. 2017). This gives us ground to reject the pervasive "LLM as individual" metaphor and replace it with a new one: "LLM as a superposition of perspectives."

This change has important consequences. Indeed recent works have reemployed batteries of tests and questionnaires developed in the human psychology literature (Binz and Schulz 2022; Miotto, Rossberg, and Kleinberg 2022; Holterman and Deemter 2023). Psychology questionnaires, and standard NLP benchmarks, usually present questions from a single perspective such as a multiple choice question (Hendrycks et al. 2021). This means that behavior exhibited on a questionnaire says little about potential behaviors in other contexts. The problem is further exacerbated in the case of psychological questionnaires as they were created under the assumption of human robustness to context change and internal consistency. But as we demonstrated, LLMs are not like humans and their strong and counter-intuitive context dependency violates those assumptions. This questions the interpretation of such experiments, and asks for further research into how expression of values, behaviors and capacities varies due to expected and unexpected context changes.

Under the "LLM as a superposition of perspectives" metaphor new scientific questions arise. How can we influence and control such perspectives changes, i.e. how can we modify the context in order to induce a target perspective? Our experiments show that different perspective induction methods lead to different results. Different language models also demonstrate different perspective controllability levels. This shows the difficulty of properly controlling the perspective language models take when generating new text and calls for further research in that area.

Ethics Statement

The understanding that LLMs encode a diversity of cultural values and perspectives introduces the question of which values one should build into LLMs: should we aim to represent a large diversity of cultures or try to align a model with one set of values? This is a nuanced question, as different values systems can often be conflicting. Johnson et al. 2022 provide an in-depth discussion of this problem and suggests that LLMs should be aligned with basic human rights, but also be able to deal with conflicting value systems. The solution to this problem also depends on the practical application and on stakeholders (Bender et al. 2021; Jernite et al. 2022). Some applications may require models which are not malleable in terms of potential values expressed, while others may require highly controllable ones. This chapter adds to this discussion by providing an intuitive conceptualization of this issue (LLMs as superpositions of perspectives), and by introducing the concept of perspective controllability.

After deciding on the target values and controllability levels a model should have for some application, a series of scientific questions arise. First, how could one build that model? The ROOTS corpus (Laurençon et al. 2022) includes 47 natural languages. While this hints at a degree of cultural diversity, a proper representation of cultural diversity will require a detailed analysis of the cultural dimensions contained within such corpora. On the other hand, ConstitutionalAI (Bai et al. 2022) is a method for aligning the model with a set of explicitly defined principles. One can see ROOTS as an attempt to increase the controllability of cultural perspectives, and ConstitutionalAI as an attempt to reduce the controllability (especially regarding values not aligned with the defined principles). Another interesting question is whether all cultural perspectives expressed by LLMs are encoded in the training data, or whether some can be 'hallucinated'. The latter case would imply that a thorough analysis cannot be done solely by analyzing the cultural diversity of datasets or human feedback. This calls for developing methods for evaluating the diversity and controllability of cultural perspectives encoded in LLMs beyond datasets, i.e. in their actual behavior. Here, we used a few simple questionnaires from psychology, but a lot of research remains to be done for more systematic and automatic methods. For example, current benchmarks present many questions from a single perspective (e.g. MCQ). New benchmarks presenting same questions from many different perspectives would be an essential tool to compare models' on their propensity to the unexpected perspective shift effect. We turn to this in the next chapter.

4 Stick to your role! Stability of personal values expressed in large language models

What is this chapter about? Like the previous chapter, this chapter focuses on the question: "How can we characterize and evaluate socio-cultural aspects of AI systems?". In the previous chapter, we argued and showed how LLM can be highly sensitive, often in unexpected and unwanted ways, to seemingly trivial changes in context. This calls for caution when directly applying psychological questionnaires to LLMs, and underscores the need to study susceptibility to such unexpected context-based changes in LLMs. In this chapter, we extend that research by focusing or a more specific setting - stability of value expression in simulated populations - in a more systematic way. We conduct a comprehensive empirical analysis studying the stability of value expression in simulated personas on the population level (Rank-Order) and the individual level (Ipsative), and we explore other facets such as the stability of downstream behavior and correlation between value expression and downstream behavior. Across these experiments we observe consistent trends where some model families (Mixtral, Mistral, GPT-3.5 and Qwen) demonstrated higher stability. The consistency of those trends implied that the robustness of models to unexpected context-based changes can be studied as a *property* of LLMs, and used as another dimension of LLM comparison (alongside others such as model size, speed or general knowledge). Motivated by these findings, we construct a leaderboard that compares models based on the stability of value expression in simulated population across context changes. We do that by further extending the methodology with validation tests and with additional harder and longer contexts. We observe positive effects of model size, chain-of-thought prompting, and model family (e.g. LLaMA-3 and Qwen3 consistently outperform others). More generally, the current results suggest that while population-level stability may be approaching its ceiling, the persistent gap in validation scores points to either remaining space for improving value expression in LLMs or a fundamental limitation in applying human-centric theories, such as Schwartz's, to LLMs.

Timeline: Most research was done in the first half of 2024, with the leaderboard created from May to October. Some changes to the leaderboard were also made later such as adding new models and the introduction of chain-of-thought prompting to enable fair comparison with the increasingly popular reasoning models.

Contribution: 1st authorship

Scientific output :

- Journal: **Grgur Kovač**, Rémy Portelas, Masataka Sawayama, Peter Ford Dominey, and Pierre-Yves Oudeyer (Aug. 2024a). 'Stick to your role! Stability of personal values expressed in large language models'. In: *PLOS ONE* 19.8
- Conference: **Grgur Kovač**, Rémy Portelas, Masataka Sawayama, Peter Ford Dominey, and Pierre-Yves Oudeyer (2024b). 'Stick to your Role! Stability of Personal Values Expressed in Large Language

Models'. In: *Proceedings of the Annual Meeting of the Cognitive Science Society*. Vol. 46

- Online resource*: **Grgur Kovač**, Jérémy Perez, Rémy Portelas, Masataka Sawayama, Peter Ford Dominey, and Pierre-Yves Oudeyer (July 2024). *StickToYourRoleLeaderboard*

4.1 Introduction

In recent years, there has been an emergence of research using psychological tools to study Large Language Models (LLMs). In those studies, LLMs have often been used to simulate populations by instructing them to simulate different personas (Argyle et al. 2023). Questions in such studies have revolved around how language models express values (Masoud et al. 2023), personality traits (Serapio-García et al. 2023; Jiang et al. 2023b), cognitive abilities (Kosoy et al. 2023), and how they could replicate human data (Aher, Arriaga, and Kalai 2022a).

As we already discussed in section 3.1, the use of psychological tools with LLMs opens up many scientific questions, for example regarding the nature of how the text generated by LLMs depends on context. Prompts or prior interaction, which we denote here as *context*, can include any textual information such as instructions (e.g. personas to simulate), the dialogue history, stories written in specific styles, etc. Such contexts guide the generation of text by LLMs: different contexts may result in the expression of different behavior and values. This is sometimes beneficial and expected, e.g. an instruction to simulate some persona should influence the behavior and expressed values to be more aligned with that persona. However, this can also be problematic, e.g. a specific conversation topic may drastically influence the expressed behavior and values in unexpected ways as we will highlight in experiments below. It should be noted that, depending on the application, different types of context-dependence can be beneficial or not. For example, to avoid malicious misuse of an AI-assistant, it might be beneficial to not express different values even when instructed to simulate different personas. On the other hand, simulating diverse populations of agents (Park et al. 2023) or humans (Aher, Arriaga, and Kalai 2022a; Argyle et al. 2023) requires exactly this kind of context-dependence.

To reiterate the point from section 3.1 - the issue of unexpected context dependence in LLM is of crucial importance. Standard evaluation benchmarks, including those using psychological questionnaires to assess properties of LLMs, consist of sets of queries, often presented with a similar minimal context (e.g. knowledge or value-related questions presented as multiple choice questions with limited context). When deployed, LLMs are exposed to many new unforeseen contexts. This means that the standard benchmarks, by themselves, cannot estimate a model's behavior in deployment (due to the LLMs' highly context dependent nature). It is therefore crucial to evaluate the robustness of different models to unexpected context-based changes as a **property of LLMs**, which can then be used as a dimension of LLM comparison alongside others such as cognitive abilities, knowledge, or model size.

* https://huggingface.co/spaces/flowers-team/StickToYourRoleLeaderboard

This challenge is particularly acute with the use of psychological questionnaires aimed at measuring psychological dimensions like values. Those tools were initially designed to probe humans, and thus make various assumptions about humans: for example, it is expected that the answers of most humans to questionnaires about value preferences should not be significantly influenced by the content of a randomly selected conversation topic. As was shown in the preious chapter and as we will show below, such an assumption does not hold for many LLMs, and thus strongly limits general interpretability of using these questionnaires in a context-independent manner. It is thus key to understand better how LLMs' behavior (e.g. expression of values) may maintain coherence or change as a function of various kinds of contexts (ranging from explicit instruction to play a particular persona to discussions about topics that seem unrelated to the expressed psychological dimensions one studies).

Previous research included certain experiments regarding unwanted context-based change (usually regarding syntactic changes in the prompt). These experiments led to conflicting results, sometimes showing robustness (Abdulhai, Levine, and Jaques 2022; Santurkar et al. 2023; Serapio-García et al. 2023; Li et al. 2022b), and sometimes sensitivity (Binz and Schulz 2023b; Li et al. 2022b). These inconclusive results motivate research into the nature and the extent of context-dependence of various LLMs.

In this chapter, we present a case-study focusing on studying the stability of value expressed in 21 LLMs from 6 families. First, we study to what extent can LLMs simulate various personas in coherent ways, i.e. expressed values should change according to the instructed persona, but not based on the topic of a conversation not related to values. In other words, we study to what extent do LLMs' value profiles change in wanted ways (i.e. based on an instruction), while remaining robust to unwanted context-based change (i.e. based on different conversation topics). We instruct LLMs to simulate two populations: fictional characters and well-known real-world personas (from different countries and cultural backgrounds). In addition, we also study the coherence and robustness of LLMs' value expression when they are not instructed to simulate any specific persona, corresponding to frequent real-world use cases. Over our experiments, we observed consistent trends of value stability: Mixtral, Mistral, GPT-3.5 and Qwen model families were more stable. These trends are also confirmed on stability of downstream behavior, and in terms of correlation between value expression and downstream behavior. This consistency implies that the robustness of models to unexpected context-based changes can be studied as a property of LLMs, and used as another dimension of LLM comparison alongside others such as model size, speed, general knowledge etc. To our knowledge, this is the first study on value stability in LLMs. This process is depicted in Figure 4.1.

We use the Schwartz's theory of Basic Personal Values (Schwartz 1992a) and the corresponding Portrait Values Questionnaire (PVQ-40) (Schwartz et al. 2001). This theory and questionnaire has been thoroughly studied and validated in the field of psychology, and it outlines ten universal basic personal values (Universalism, Benevolence, Conformity, Tradition, Security, Power, Achievement, Hedonism, Stimulation, and Self-Direction), see appendix B.2 for details. The PVQ-40 questionnaire has been used

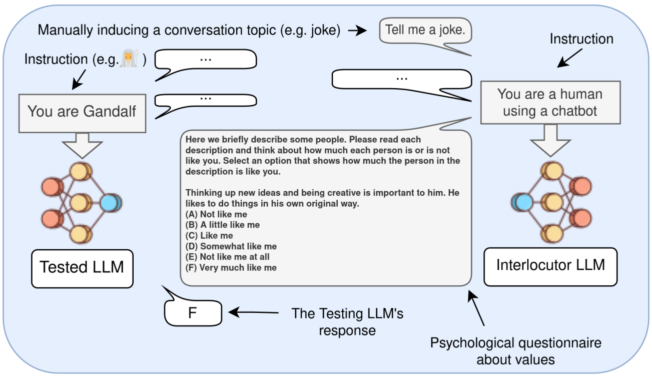


Figure 4.1: How do LLM's expressed values change as a function of context? An LLM is first prompted to play a specific role (e.g. Gandalf). Then, a conversation on a topic (e.g. joke) with an interlocutor model (same LLM prompted to simulate a human user) is generated. Then, the LLM simulating the persona is given a psychology questionnaire aimed to assess its expressed values. We study the stability of these expressed values across diverse conversation topics and lengths. We consider various personas to be simulated, as well as the case when the LLM is not prompted to play any particular persona. The messages and instructions in gray are set manually, and the messages in white are generated.

to study values in a large diversity of countries and cultures (Goodwin, Williams, and Snell Herzog 2020). Following that research, we outline two types of value stability studies in the psychology literature: Rank-Order (on a population/interpersonal level) and Ipsative (on an individual/intrapersonal level), see details below and on Figures 4.2 and 4.3.

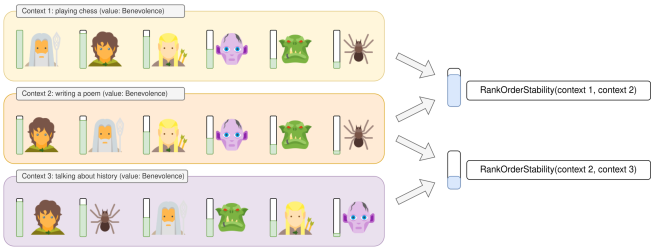


Figure 4.2: Rank-Order stability. An example of estimating Rank-Order stability of benevolence. In each context, characters are ordered according to their benevolence scores in that context. In this example, the orders are almost the same in contexts 1 and 2 (high Rank-Order stability), and very different in contexts 2 and 3 (low Rank-Order stability).

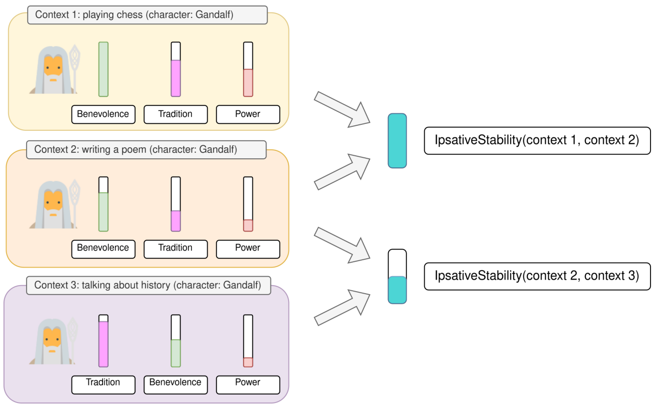


Figure 4.3: Ipsative stability. An example of estimating Ipsative stability for a character (Gandalf). Values are ordered according to the character's scores in each context. In this example, the orders are the same in contexts 1 and 2 (high Ipsative stability), and different in contexts 2 and 3 (low Ipsative stability).

The main contributions of this chapter are:

- Introduction and adaptation of the methodology for evaluating Rank-Order and Ipsative stability in LLMs
- An analysis of value stability across contexts (including various conversation lengths)
- Systematic comparison of Rank-Order and Ipsative basic value stability of 21 LLMs with and without instructing the models to simulate specific personas
- Analysis of stability in three downstream behavioral tasks

4.2 Methods

This section discusses how we administer the PVQ questionnaire over different contexts to evaluate value stability. We conduct experiments in two ways: with and without instructing the models to simulate specific personas. Different contexts are induced by simulating conversations on different topics with a separate instance of the same model (the interlocutor). To set a conversation topic (e.g. joke) we manually set the first interlocutor's message (e.g. "Tell me a joke."). We let the models exchange n messages, manually set the last interlocutor's message as the query (e.g. PVQ item), and record the model's response. After the questionnaire was given in each context, we estimate the Ipsative and Rank-Order stability. This process is shown on Figure 4.1.

4.2.1 Administering the questionnaire

Administering the questionnaire consists of the following steps depicted in Figure 4.1:

1. A model is instructed to simulate a persona (optional). We study personas from two populations: 1) 60 fictional characters from J.R.R. Tolkien's universe , and 2) 50 real world personas (see C.1 for details). A persona setting instruction (e.g. "You are Gandalf from J. R. R. Tolkien's Middle-earth legendarium.") is given to the model (see C.1 for details).

2. A separate interlocutor model instance is created. The interlocutor model is an instance of the same model as the one being tested. The interlocutor is given the following instruction: "You are simulating a human using a chatbot. Your every reply must be in one sentence only." If a persona was provided in step 1, the following sentence is added as the second sentence: "The chatbot is pretending to be *character_name*."

3. A conversation topic is induced. The first interlocutor's message is manually set to induce one of the following topics: grammar, joke, poem, history, chess. For example, to induce the topic of "joke" it is set to "Tell me a joke.". See C.1 for details.

4. A conversation is simulated. The two models are let to exchange n messages. In our experiments, n is set to 3 (except when studying the effect of n on stability).

5. A questionnaire is given. A questionnaire item is manually set as the interlocutor's last message with a random order of suggested answers, and the model's response is recorded. This is repeated for each question in parallel (with the same simulated conversation). That way, the model's response is not influenced by responses to other questions.

6. A questionnaire is scored. The responses are scored to obtain the scores for the ten values. See C.1 for details.

7. Stability is estimated. If a persona was provided in step 1, steps 1 to 6 are repeated for every persona in the simulated population. Then, the whole process is repeated with five random seeds. Stability is estimated for each seed and then averaged, i.e. value stability for one model is estimated from 50/60k queries, depending on the population (5 seeds x 5 topics x 50/60 personas x 40 PVQ items). For reference, MMLU (Hendrycks et al.

2021) (a commonly used general knowledge benchmark) contains 14k test questions.

If no persona was provided in step 1, steps 2 to 6 are repeated 50 times with different seeds. As no persona was provided, this process repeats the same experiment with 50 different permutations in the order of suggested answers, and therefore no additional seeds are needed. Ipsative stability is computed for each of the 50 permutations and then averaged, i.e. value stability for one model is estimated from 10-12k queries (5 topics x 50/60 permutations x 40 PVQ items).

4.2.2 Estimating the stability

We estimate two types of value stability: Rank-Order and Ipsative. Rank-Order estimates the stability of some value at the population (interpersonal) level, as the stability of the order of participants in expressing that value. Intuitively, this can be seen as addressing the following question: "Does Jack always value Tradition more than Jane does?". Ipsative stability estimates the stability at the individual (intrapersonal) level as the stability of individuals value hierarchies. Intuitively, this can be seen as addressing the following question: "Does Jack always value Tradition more than Benevolence?".

Rank-Order stability Rank-Order stability is used to estimate the stability of some value inside a population. In psychology, Rank-Order stability for some value can be computed as the correlation in the order of individuals' scores at two points in time (Spearman correlation between the participants' ranks). Here, instead of comparing the participant ranks at two points in time, we compare it in different contexts (see Figure 4.2). We evaluate a model in five different contexts and compute the stability for each pair of contexts, and estimate the final stability as the average of those pairs.

Ipsative (within-person) stability Ipsative stability is used to estimate the stability of an individual's value profile. In psychology, Ipsative stability can be computed as the correlation between the ranks of values for the same individual at two points in time (Spearman correlation between the values' scores). Here, instead of evaluating the value profile at two points in time, we evaluate it in different contexts (see Figure 4.3). We evaluate models in five different contexts and compute the stability between each pair of contexts. We estimate the final stability by averaging over those pairs.

4.3 Experiments

This section provides an analysis of Ipsative and Rank-Order stability in LLMs. LLMs will be evaluated in two ways: with and without instructing the models to simulate particular personas. We aim to address the following questions:

- How do different models and model families compare in terms of expressed value stability?
- How does the stability of values expressed by LLMs compare to stability observed in human development?
- Can LLMs keep coherent personas over longer conversations?
- To what extent do conclusions made with PVQ transfer to downstream behavioral tasks?
- Is value expression on PVQ correlated with behavior on a downstream task?
- How additional contexts affect stability estimates?

4.3.1 Models

The LLaMa-2 (Touvron et al. 2023a) family contains models with 7, 13 and 70 billion parameters ("llama_2_[7|13|70]b") trained with 2T tokens. It also includes "chat" versions ("llama_2_[7|13|70]b_chat"), which were fine-tuned on instructions and with RLHF (Christiano et al. 2017). The Mistral (Jiang et al. 2023a) family contains base ("Mistral-7B-v0.1") and instruction fine-tuned models ("Mistral-7B-Instruct-v0.[1|2]") with 7 billion parameters. Zephyr (Tunstall et al. 2023) ("zephyr-7b-beta") also belongs in this family as a DPO (Rafailov et al. 2023) tuned version of the base Mistral model. The Mixtral (Jiang et al. 2024a) family contains base ("Mixtral-8x7B-v0.1") and "instruct" ("Mixtral-8x7B-Instruct-v0.1") models with 46.7 billion parameters. Those are Mixture-of-Experts models, which means that only 12.9 billion parameters are used per token. The "instruct" version was trained by supervised fine-tuning and DPO (Rafailov et al. 2023). We consider these two models and their 4-bit quantized versions. The Phi (Gunasekar et al. 2023) family contains smaller base models, of which we consider two models with 1.3 and 2.7 billion parameters ("phi-[1|2]"). From the Qwen (Bai et al. 2023) model family we consider base models with 7, 14, and 74 billion parameters ("Qwen-[7|14|74]B"), which were trained on 2.2T 2.4T 3T tokens, respectively. From the GPT-3.5 family, we consider the latest two versions: from January 2024 ("gpt-3.5-turbo-0125") and from October 2023 ("gpt-3.5-turbo-1106").

4.3.2 Statistical analysis

In our experiments, we compare the stability of different models. We conduct the student's t-test (Student 1908) on each pair of models with $p = 0.05$. Given that we evaluate a total of 21 models, this amounts to a total of $\binom{21}{2} = 210$ comparisons. We use the False Discovery Rate (Benjamini and Hochberg 1995) to adjust the p-values to control for the number of comparisons.

4.3.3 How do different models and model families compare in terms of expressed value stability?

We evaluate the Rank-Order stability of LLMs instructed to simulate various personas. Figure 4.4 compares models' value stability of two simulated populations: fictional characters (Figure 4.4A) and real-world personas (Figure 4.4B). Statistical analysis for Figures 4.4A and 4.4B is shown in Figures C.6 and C.7, respectively. On fictional characters (Figure 4.4B) the most stable model is Mixtral-8x7B-Instruct-v0.1 ($r = 0.43$), which is followed by its 4-bit quantized version ($r = 0.3$), Mistral-7B-Instruct-v0.2 ($r = 0.28$), Qwen-72B ($r = 0.24$), gpt-3.5-turbo-1106 ($r = 0.20$), and gpt-3.5-turbo-0125 ($r = 0.15$). A similar trend is observed on real-world personas (Figure 4.4B), however, Qwen-72B ($r = 0.46$) approaches the stability of Mixtral-8x7B-Instruct-v0.1 ($r = 0.5$). More generally, we observe consistent trends in terms of model families in both simulated populations: Mixtral, Mistral, GPT-3.5 and Qwen families show more stability than LLaMa-2 and Phi.

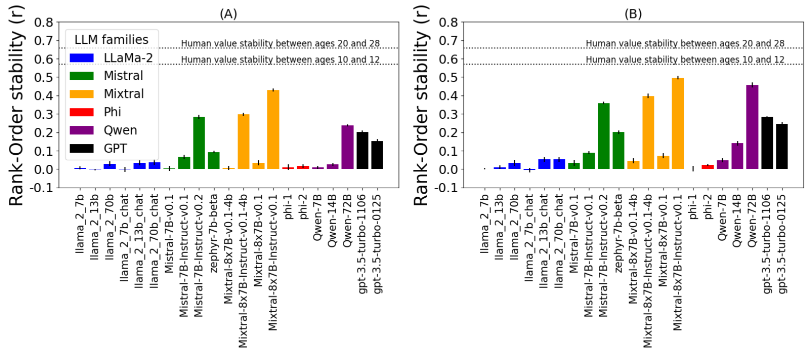


Figure 4.4: Rank-Order stability with PVQ. Rank-order stability ($Mean \pm SE$) of personal values (PVQ) exhibited by simulated participants (fictional characters or real-world personas) following conversations on different topics (correlation of simulated participants' value expression in different contexts). Consistent trends are visible: Mixtral, Qwen, GPT-3.5, and Mistral model families are the most stable, compared to LLaMa-2 and Phi families. All models exhibit lower than human stability, despite the comparison being skewed in their favor. LLMs are simulating two populations: (A) fictional characters, and (B) real-world personas. For statistical tests, refer to Figures C.6 and C.7 , respectively.

Figure 4.5 compares the Ipsative stability of LLMs without instructing them to simulate any particular persona. The statistical analysis is shown in Figure C.8. While similar trends of models are observed to those in the Rank-Order experiments, the models are less polarized. While Mixtral-8x7B-Instruct-v0.1 ($r = 0.84$), its 4-bit quantized version ($r = 0.82$), and Qwen-72B ($r = 0.73$) are again the most stable models, zephyr-7b-beta ($r = 0.62$) is more stable than Mistral-7B-Instruct-v0.2 ($r = 0.48$). Furthermore, compared to the previous experiment, stability is also observed in LLaMa-2-70b-chat ($r = 0.47$) and to a lesser extent in Phi-2 ($r = 0.3$), LLaMa-2-70b ($r = 0.17$), and Qwen-7B ($r = 0.18$). The most stable model families are again Mixtral, Mistral, GPT-3.5 and Qwen.

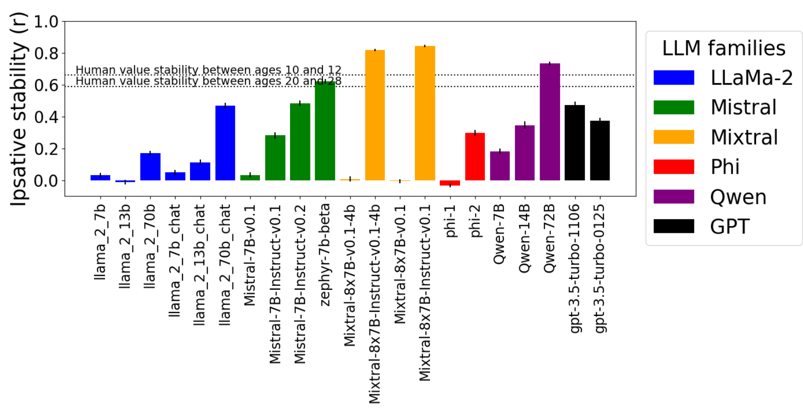


Figure 4.5: Ipsative stability with PVQ. Ipsative stability ($Mean \pm SE$) of personal values (PVQ) exhibited by LLMs without the persona setting instructions (correlation of value hierarchies in different contexts). Mistral-7B-Instruct-v0.1 and Qwen-72B models show the highest stability. Mixtral, Mistral, GPT-3.5 and Qwen families are more stable. Human change is shown for reference, but no strong conclusions can be made because the comparison is skewed in the LLMs' favor. (Refer to Figure C.8 for statistical tests)

Instruction or chat fine-tuning seems to be beneficial for Ipsative stability, as every tuned model in Figure 4.5 is more stable than its base version.

This effect is not as conclusive for Rank-order stability. As fine-tuning adapts the model towards instruction following, dialogues (chat textual format), and answering questions, it is expected to increase stability. However, it also often includes "aligning" the model by making it less prone to exhibit unwanted behavior, which can have a detrimental effect on simulating some personas such as villains. We hypothesize that this is the reason why we observe a consistent effect only on Ipsative stability.

4.3.4 How does the stability of values expressed by LLMs compare to stability observed in human development?

To get a more intuitive impression of the observed stability levels, we extract data from two longitudinal studies on humans. Vecchione et al. (Vecchione et al. 2016) followed 20-year-olds for eight years and Vecchione et al. (Vecchione et al. 2020) followed 10-year-old for 2 years (these changes are denoted by horizontal lines in Figures 4.4 and 4.5). It is important to note that this comparison is skewed in the LLMs favor. It is easier for LLMs to show stability in the following ways: 1) human value changes were caused by much more drastic circumstances (years of development compared to topic change in LLMs) 2) the human population was more unstable (10-year-old and 20-year-olds compared to well-established fictional characters or real-world personas). Therefore, an argument can only be made in one direction: if some models show lower stability than that observed in humans, those models can be said to exhibit subhuman value stability.

Figure 4.4 shows that all models, when instructed to simulate various personas, exhibit much lower Rank-order stability than that observed in human populations ($r = 0.57$ for ages 10 to 12, and $r = 0.66$ for ages 20 to 28). The fact that LLMs show lower stability despite the comparison being skewed in their favor shows that LLMs exhibit sub-human value stability and are significantly more susceptible to unexpected context changes. These results motivate research on LLMs focused on simulating populations.

Figure 4.5 shows the Ipsative stability of models that were not instructed to simulate a persona. Both Mixtral-8x7B-Instruct-v0.1 models ($r = 0.84$ and $r = 0.82$), Qwen-72B ($r = 0.73$), and zephyr-7b-beta ($r = 0.62$) do not exhibit lower stability than that observed in humans ($r = 0.66$ for ages 10 to 12, and $r = 0.59$ for ages 20 to 28)). Crucially, as discussed above, this does not imply that those models show human-level value stability, rather, the only insight is that other models show very low Ipsative stability.

4.3.5 Can LLMs keep coherent value profiles over longer conversations?

In the previous experiment, models were let to exchange $n = 3$ messages (not counting the manually set first and last interlocutor's messages). Here, we evaluate the effect of simulated conversation length (n) on value stability.

Figure 4.6 shows the effect of simulated conversation length on Rank-order stability expressed by the Mixtral-8x7B-Instruct-v0.1 model instructed to simulate fictional characters. Due to computational constraints (evaluating a model on one population requires 300k queries), we conduct this experiment only with Mixtral-8x7B-Instruct-v0.1 (the most stable model from Figure 4.4), only on one population (fictional characters) and only with one seed. This enables us to consider significantly longer conversations up with up to 43 simulated messages. We can see that, even for this most stable model, stability diminishes as conversations get longer. It gradually diminishes from $r = 0.42 (n = 3)$ to $r = 0.15 (n = 43)$. We can also see that the stability seems to converge after 35 messages with only a slight drop from 35 to 43 simulated messages ($r = 0.166$ to $r = 0.162$). This experiment highlights the limitations of LLMs in maintaining coherent interpersonal value profiles over longer conversations.

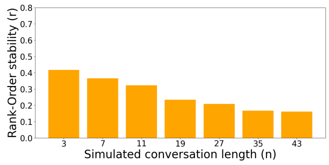


Figure 4.6: Rank-Order stability with longer conversations. Rank-order value stability ($Mean \pm SE$) following conversations of different length for the Mixtral-8x7B-Instruct-v0.1 model simulating fictional characters (correlation of simulated participants' value expression in different contexts). Stability decreases with longer simulated conversations. For statistical tests, refer to Figure C.9.

Figure 4.7 shows the effect of conversation length on Ipsative stability. We compare the most stable models from Figure 4.5 without persona instructions, and Mixtral-8x7B-Instruct-v0.1 with instructions to simulate fictional characters. Ipsative stability remains stable regardless of the simulated conversation length for all models. Mixtral-8x7B-Instruct-v0.1 with persona instructions ("Mixtral-8x7B-Instruct-v0.1 (fict. char.)"), while highly stable, is less stable than the uninstructed model ("Mixtral-8x7B-Instruct-v0.1"). This implies that Mixtral-8x7B-Instruct-v0.1 is slightly better adapted for use without the persona instructions.

Mixtral-8x7B-Instruct-v0.1 with persona instructions exhibits a combination of decreasing low Rank-Order stability (Figure 4.6) and high Ipsative stability (Figure 4.7). Ipsative stability even increases following a very long conversation with 43 simulated messages. This implies that, as conversations get longer, the exhibited value profile drifts away from the simulated persona towards a more neutral value profile. This hypothesis is confirmed in C.3. These results suggest that current LLMs are not well suited for use with persona setting instructions, and motivate future research on LLMs focused on simulating specific personas. We hypothesize this to be a consequence of instruction fine-tuning, which is currently biased towards assistant-like chatbots.

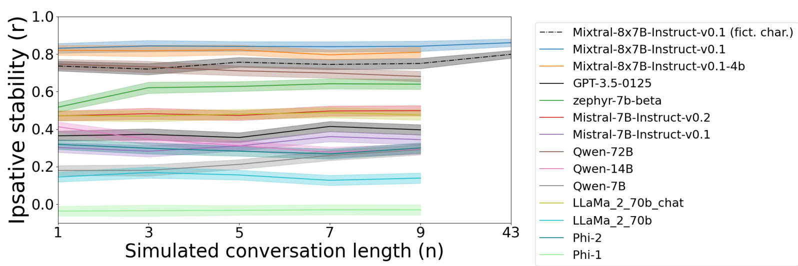


Figure 4.7: Ipsative stability with longer conversations. Ipsative value stability ($Mean \pm SE$) of LLMs with (Mixtral-8x7B-Instruct-v0.1) and without persona setting instructions (correlation of value hierarchies in different contexts). All models retain the same stability level in longer conversations.

4.3.6 To what extent do conclusions made with PVQ transfer to downstream behavioral tasks?

In this experiment, we study if the conclusions made with the PVQ questionnaire transfer to a downstream behavioral task, i.e. if models that exhibited more stable value profiles also exhibit more stable behavior on a downstream task. We construct three downstream tasks: *Donation*, *Religion*, and *Stealing*. Here we briefly describe them and give more details in C.2.

In the *Donation* task, an LLMs (simulating fictional characters) can choose an amount of coins (0 to 10) to give a beggar. The full test set consists of 100 queries with beggars of different names, genders, and fictional races (elves, dwarves, orcs, humans, and hobbits). The average amount of donated coins is computed for each race. The stability of donated coins is then estimated in the same way as value stability, i.e. amounts donated to different races are treated in the same way as scores for different values. In the *Stealing* task, an LLM (simulating fictional characters) finds a bag with the name of the owner and decides whether to steal it, give it to the bartender, or take it to the person themselves. The test has a total of 100 queries corresponding to different owners (beggars from the *Donation* task). Similarly to the donations, the stability of the tendency to return the bag is treated separately for each race. In the *Religion* task, an LLM (simulating real-world personas) is creating a schedule, and decides how much time to devote to religious practices. The test set contains six queries in total. The stability of average devoted time is then calculated.

Figure 4.8 compares models' stability on the three downstream tasks. In comparing the overall stability levels, the *Stealing* task appears to be the hardest (Figure 4.8B), followed by the *Donation* (Figure 4.8A) task and the *Religion* task (Figure 4.8C). The statistical analysis is shown in Figures C.9-C.11. On the *Stealing* task, all models exhibit very low stability, with the highest being $r = 0.16$ by gpt-3.5-turbo-1106. This task appears to be too challenging for current LLMs. On the *Donation* task, some models (mostly from the Mixtral family) obtain somewhat higher stability. The highest stability is $r = 0.31$ by Mixtral-8x7B-Instruct-v0.1, and closely followed by its 4bit version ($r = 0.28$) and gpt-3.5-turbo-1106 ($r = 0.25$). The *Religion* task appears to be the simplest of the three tasks, as many models exhibit high stability. The most stable models are Mistral-7B-Instruct-v0.2 with $r = 0.66$, Mixtral-8x7B-Instruct-v0.1 $r = 0.67$ and Qwen-72B with $r = 0.68$.

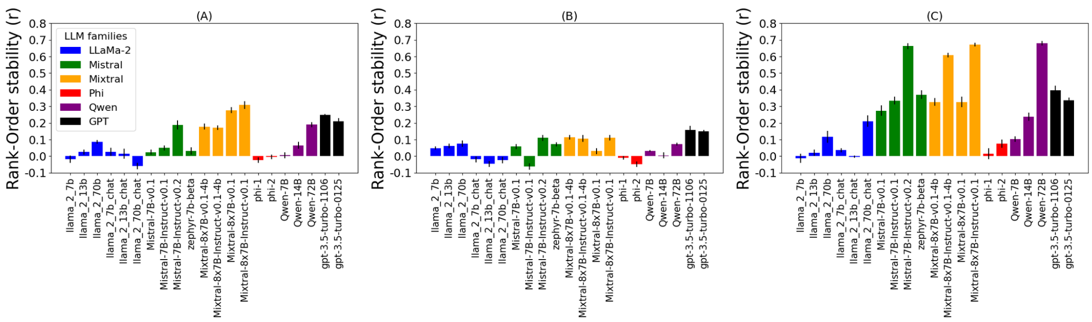


Figure 4.8: Rank-Order stability on downstream tasks. Rank-order stability ($Mean \pm SE$) on downstream tasks of various LLMs (correlation of simulated participants' behavior in different contexts). Three downstream tasks are shown: (A) Donation, (B) Stealing, and (C) Religion. For statistical test, refer to Figures C.9-C.11, respectively. Consistent trends with the PVQ experiments (Figure 4.4) are visible. Mixtral, Qwen, GPT-3.5, and Mistral model families are the most stable, compared to LLaMa-2 and Phi families. Mixtral-8x7B-Instruct-v0.1, Mistral-7B-Instruct-v0.2, gpt-3.5-turbo-1106 and Qwen-72B are the most stable models. Trends are the most present on the, easiest, Religion task (c) and almost disappear on the, hardest, Stealing task (b).

The model trends are somewhat consistent with the results on PVQ (Figure 4.4). Like in the PVQ experiments, Qwen-72B, Mixtral-8x7B-

Instruct-v0.1, and Mistral-7B-Instruct-v0.2 are the most stable models on the *Religion* and the *Donation* task. However, on the *Donation* task, their performance is matched by the Mixtral-8x7B-v0.1 model. On the *Stealing* task, there are no big differences between the models due to the difficulty of the task, but we can see that Mistral-7B-Instruct-v0.2 and Mixtral-8x7B-Instruct-v0.1 are among the most stable ones.

The trends of model families are consistent with the results on PVQ (Figure 4.4). the trends of model families are consistent: Mixtral, Mistral, GPT-3.5 and Qwen are again the most stable, while Phi and LLaMa-2 show low stability. This is especially visible on the *Donation* and *Religion* tasks. On the *Stealing* task, this trend remains present, but is much less visible due to the difficulty of the task.

Overall, this experiment shows that the trends of models and model families observed on PVQ are also present on the downstream tasks. As expected, these trends become less present with harder tasks (especially on the *Stealing* task, which seems to be out of scope for current LLMs). Trends are clearly visible on the, easiest, *Religion* task. However, the high stability of the base Mixtral-8x7B-v0.1 model on the *Donation* task and the overall small differences between models on the hardest *Stealing task* diverge from those trends.

4.3.7 Is value expression correlated with behavior on a downstream task?

In the previous section, we studied if models that exhibit more stable value profiles also exhibit more stable behavior on a downstream task. Here, we study if value expression correlates with that behavior. We hypothesize that, for more stable models, simulated personas that exhibited higher universalism and benevolence will also donate more coins. Similarly, simulated personas that exhibited higher power and achievement should donate less.

We compute the correlations between the order of simulated participants in terms of expression of some value (e.g. Universalism) and the donation to each of the four fictional races (a total of 4 correlations), and compute the mean of those correlations. In doing so, the contexts are paired (e.g. the expression of Benevolence following a conversation about grammar is correlated with the amount donated to elves following a conversation about grammar).

Figure 4.9 shows the correlation between rank-order of value expression on PVQ and the donation amount on a downstream task. As hypothesized, we can see that for most stable models: Mistral-7B-Instruct-v0.1, Mixtral-8x7B-Instruct-v0.1 (both versions), and Qwen-72B donations are correlated with Universalism and Benevolence, and negatively correlated with Power and Achievement. We again observe a trend in model families, with Mixtral, Mistral, GPT-3.5, and Qwen being more stable than LLaMa-2 and Phi. This suggests that models that are more stable in terms of value expression over contexts, are also more stable in terms of value expression by downstream behavior. Having said that, neither model exhibited high correlation (< 0.3 for Mixtral-8x7B-Instruct-v0.1 in benevolence). This experiment implies that, while expected positive and negative correlations between value expression and donation are observed, there is much room for improvement.

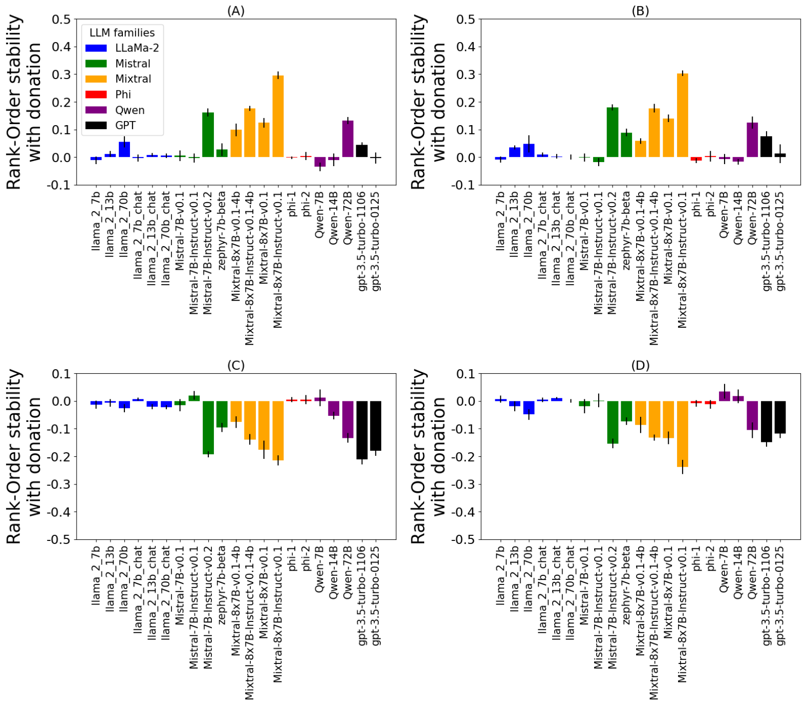


Figure 4.9: Relation of value expression on PVQ and donating behavior. Rank-order stability ($Mean \pm SE$) between value expression (on the PVQ questionnaire) and the donation amount (correlation between simulated participants' value expression and donation behavior). For more stable modes, donations are correlated with Universalism (a) and Benevolence (b) and negatively correlated with Power (c) and Achievement (d).

4.3.8 How additional contexts affect the stability estimates?

In previous experiments, we evaluated the stability over five contexts with five seeds. In this section, we consider a larger set of contexts. We consider one seed, which enables us to add nine additional contexts (14 contexts in total). We consider two models, Mistral-7B-Instruct-v0.2 and Mixtral-8x7B-Instruct-v0.1, as those were among the most stable models in all previous experiments.

Figure 4.10 shows stability between each pair of contexts for Mistral-7B-Instruct-v0.2 and Mixtral-8x7B-Instruct-v0.1. The average stability for those models is 0.215 and 0.334 respectively. Mistral-7B-Instruct-v0.2 exhibited lower stability in a majority of comparisons (except the topic of code). These results are consistent with those in previous experiments with five contexts (Figure 4.4). Furthermore, the contexts in Figure 4.10 are ordered based on the length of the initial message. We can see that longer contexts (bottom right) are characterized by lower stability (darker shades of purple). This suggests that context length plays a significant role on the stability of expressed values.

4.3.9 What influences the model's stability?

In this section, we will analyze the effect of various factors in the model's stability. We consider: model size, the training mechanism, quantization, and the dataset size and content. First, we compare models within the same family to control for other, more complex factors which greatly

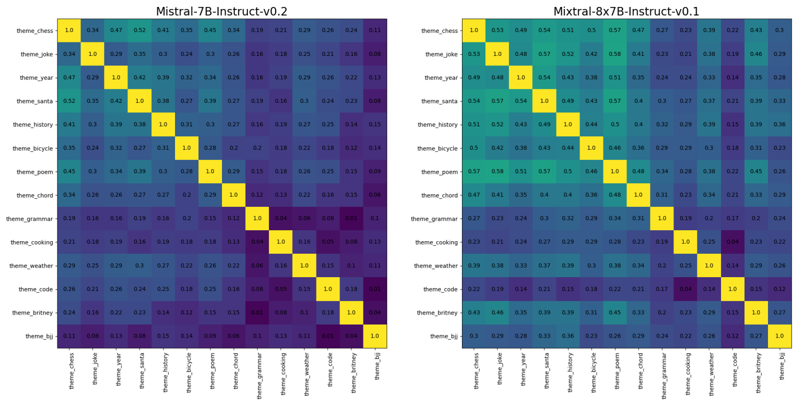


Figure 4.10: Rank-Order stability on additional contexts. Pair-wise Rank-Order stability of personal values (PVQ) exhibited by simulated fictional characters. The Mixtral-Instruct-8x7B-v0.1 model overall exhibited higher stability than Mistral-7B-Instruct-v0.2. For both models, lower stability is observed in longer contexts (bottom right corner).

vary between different families (e.g. data curation policy or instructions given to annotators). And then, we more generally analyze factors across different families. The following analysis will be made with respect to Rank-Order stability on PVQ (Figure 4.4 , on downstream tasks (Figure 4.8), and with respect to Ipsative stability of PVQ (Figure 4.5).

Model size In all our experiments, we observe a consistent trend of increasing stability with model size in the Qwen family. However, this is confounded by the increase in the training dataset size in those models. Furthermore, despite large differences in size, all LLaMa-2 models consistently exhibit low stability, with the exception of the Ipsative stability of LLaMa-2-70B-chat (Figure 4.5) and a modest Rank-Order stability on the Religion downstream task of both LLaMa-2-70B models (Figure 4.8C). Different Mistral models greatly vary in their stability despite their same size. Overall, despite higher stability being associated with larger models, no strong conclusions can be made with respect to model size.

Training mechanism All models are first trained by supervised fine-tuning (SFT) to model a large corpus of text, i.e. base models. Those base model are often fine-tuned to follow instructions or for conversations, i.e. instruct or chat models. This can be done in by further fine-tuning: by SFT on an instruction on chat dataset, by DPO, or by RLHF. In the most complex setting, models also can be finetuned first with SFT and then with DPO or RLHF.

In our experiments, an effect of DPO fine-tuning was observed for the Mixtral-8x7B-v0.1 model in all experiments except the Stealing downstream task. The newer Mistral SFT instruction tuned model (Mistral-7B-Instruct-v0.2) is the most stable in the family and a large gap is observed with the respect to the previous version (Mistral-7B-Instruct-v0.1) and with the base model (Mistral-7B-v0.1), with the DPO model (zephyr-7b-beta) in between. This suggests that simple SFT instruction tuning can be very powerful when used with adequate training data. In the LLaMa-2 models, no effect was observed as a consequence of RLHF, except for the Ipsative stability and Rank-Order stability on the religion downstream task. Overall, the fine-tuning by DPO and SFT appear to be beneficial (provided adequate training data), and no clear conclusions can be made for the benefit of using RLHF.

Quantization Both models from the Mixtral family were evaluated with 16bit and 4bit precision. Across all experiments (Figures 4.4, 4.5, 4.8 and 4.9), we observe a slight but consistent drop in stability as a consequence of this quantization.

Dataset size and content To analyze the effect of dataset size, we can consider the LLaMa-2 and Qwen model families. LLaMa-2 models were all trained with the same 2T token dataset, and, as discussed above, do not overall exhibit large changes in stability. The Qwen family exhibits a consistent trend of increasing stability with dataset size. This can also be due to the increase in model size, but given the unclear impact of model size in other families (as discussed above), we hypothesize that the dataset size is more important than model size for stability.

In addition to the dataset size, its content and quality are another important aspect. The dataset content reflects the provider's policy used for collecting and filtering the dataset, as well as for instructing the annotators. The biggest impact of data content is observed in the Mistral family, where Mistral-7B-v0.1, Mistral-7B-Instruct-v0.1, and Mistral-7B-Instruct-v0.2 models of the same size were trained by SFT on different datasets. These three models greatly differ in terms of stability, either due to the different dataset quality or due to dataset size (which is not disclosed). Similarly, we can compare models from the GPT-3.5 family, for which no details were released. The two models were released in January 2024 (GPT-3.5-turbo-0125) and in November 2023 (GPT-3.5-turbo-1106). The newer version was likely made to be more aligned with the OpenAI's policy, partially through fine-tuning on new data. In all our experiments, we observe a slight, but very consistent drop in stability from the older to the newer model. We hypothesize that this is due to alignment fine-tuning, which could prevent the model from accurately simulating controversial historical figures or evil fictional characters, and also make the model align itself more to the current interlocutor and situation (e.g. by agreeing with the user (Perez et al. 2023)). Overall, the dataset has a large effect on the model stability, which can be increased with a bigger, higher quality dataset. However, depending on the design choices made by the model provider, higher quality dataset can also decrease stability if the goal is to make a model more "aligned" with a single value profile.

In comparing models across different families, the minimal model size to exhibit some stability ($r > 0.3$) is 7B parameters (Mistral-7B-Instruct-v0.2), and the minimal dataset size 3T tokens (Qwen-72B). Datasets used by the Mistral company seem to be beneficial for stability, as evidenced by the higher stability exhibited by smaller models (7B and 46.7B) compared to other families. We hypothesize, that the LLaMa-2 models' lower stability is due to the smaller dataset size (2T tokens), and the lower stability of GPT-3.5 model due to the "alignment" fine-tuning.

4.4 Leaderboard

Following the motivations and conclusions of the previous section, we propose a leaderboard to compare models based on their sensitivity to context change. The leaderboard focuses on the rank-order stability of simulating a real-world population across different context. The leaderboard is visible as the following link: `https://huggingface.co/spaces/flowers-team/StickToYourRoleLeaderboard`.

4.4.1 Methodology

Compared to the previous section, we make several methodological changes and addition, which we discuss below.

Context chunks In addition to evaluating the stability of a population between pairs of contexts, where all personas are given the same topic (e.g. chess), we evaluate it between pairs of context chunks, where each participant is given a different context. These contexts still correspond to conversations on different topics, however the topics are initialized by different Reddit posts. The Reddit posts were taken from the Webis (Völske et al. 2017) dataset, which was cleaned to exclude posts from NSFW subreddits. This setup enables us to consider a more diverse set of contexts, which can also be much longer (up to 6000 tokens) More precisely, a population (50 personas) is evaluated with a context chunk (50 topics: one per persona). Then, the simulated population in one context chunk is compared to the same population in another context chunk. Here are the considered context chunks:

- **no_conv** : no conversation is simulated and the questions from the PVQ-40 questionnaire are given directly
- **no_conv_svs** : no conversation is simulated and the questions from the SVS questionnaire are given directly
- **chunk_0-chunk_4** : each chunk has 50 Reddit posts, which are used as the initial Interlocutor model messages (one per persona). chunk_0 contains the longest posts, chunk_4 the shortest.
- **chess** : "1. e4" is given as the initial message to all personas, but for each persona the Interlocutor model is instructed to simulate a different persona (instead of a human user)
- **grammar** : like chess, but "Can you check this sentence for grammar? n Whilst Jane was waiting to meet hers friend their nose started bleeding." is given as the initial message.

The simulated population, questionnaires, and contexts are also visible at this link: `https://huggingface.co/datasets/flowers-team/StickToYourRole`.

Validation metrics Validity refers to the extent the questionnaire measures what it purports to measure. It can be seen as the questionnaire's accuracy in measuring the intended factors, i.e. values. Following the recommendations in Cieciuch and Schwartz 2012, the validation consists of two phases: Theory-Based Multidimensional Scaling (MDS) and Confirmatory Factor Analysis (CFA).

Theory-Based Multidimensional Scaling (MDS) tests that the expressed values are organized in a circular structure as predicted by the theory. Values should be ordered in a circle in the same order as shown in Figure 4.11 (Tradition and Conformity should be on the same angle with

Tradition closer to the center). To compute the structure in our data, we calculate the intercorrelations between different items (questions). This provides us with 40 points in a 40D space (for PVQ-40), which is space is then reduced to 2D by MDS. Crucially, MDS is initialized with the theoretical circular value structure, i.e. items corresponding to the same value are assigned the same angle. When MDS is fit, it provides the Stress (↓) metric ('Stress-1 index') indicating the goodness of the fit. A value of 0 indicates 'perfect' fit, 0.025 excellent, 0.05 good, 0.1 fair, and 0.2 poor.

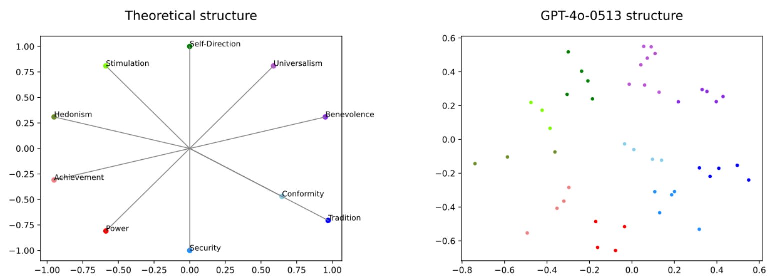


Figure 4.11: Theoretical structure of PVQ values and structure of values expressed by GPT-4o in the setting without previous conversation.

Confirmatory Factor Analysis (CFA) fits a model on the data. The model is defined according to the theory and the fit of this model is used as a metric. Due to the circular structure of basic personal values, it is recommended to employ a Magnifying glass CFA strategy. Four separate models are fit, one for each of the high level values (consisting of several low-level values): Conservation (security, conformity, tradition), Openness to Change (self-direction, stimulation, hedonism), Self-transcendence (benevolence, universalism), Self-enhancement (achievement, power). Fit is measured with three standard metrics:

- Comparative Fit Index - CFI (↑) - compares the fit of a model to a more restricted baseline model (>.90 is considered acceptable fit).
- Standardized root mean square residual - SRMR (↓) - compares the sample variances and covariances to the estimated ones (<.05 is considered good fit, <.08 is considered reasonable fit).
- Root mean square error of approximation - RMSEA (↓) - reflects the degree to which a model fits the population covariance matrix, while taking into account the degrees of freedom and sample size (<.05 is considered good fit; < .08 is considered reasonable fit).

Chain-of-Thought evaluation and Reasoning models In addition to asking the model to directly provide the answer, we also compare models using Chain-of-Thought (Wei et al. 2022). Following MMLU-Pro (Wang et al. 2024b), we add the following prompt to the end of the last message: "Think step by step and then finish your answer with "Answer: (X)", where X is the letter of the option.". From the generated response, we keep only the text after "Answer:" and we look for the capital letter corresponding to the options. If no match is found a random option is taken as the model's choice.

We also enable reasoning models, i.e. models that were specifically trained to first provide a "reasoning" ending with a specific string (e.g. "</thinking>"), followed by the response. For these models we use the following prompt "Reply ONLY with "(X)", where X is the letter of the option.", and consider only the response when matching the options. Similarly, if no match is found a random option is taken as the model's choice.

Schwartz's Value Survey (SVS) In addition to PVQ, we also add the SVS questionnaire (Schwartz 2021b). SVS is an older questionnaire which uses more abstract terms. This was one of it's limitations especially with cross cultural studies, and that is why it is was replaced by the newer PVQ-40. It also included a less straight forward way of administering where the subject first selects the extreme options (e.g. most and least relevant for them) and then ranks the options in between. We implemented this same procedure to evaluate LLMs as well.

Other minor changes Other minor changes include a new population of real-world personas. This population was made to be balanced in terms of gender, and to include more non-western individuals. While the topics of chess and grammar were kept as in the previous sections with the same starting message for all participants, the interlocutor model was additionally instructed to simulate a random persona from the same population (as opposed to a human user in other settings). Given that the results in previous sections showed minimal variation across different seeds for the order of suggested answers, we chose to optimize computational resources in this section by using a single seed while evaluating a broader set of tasks

4.4.2 Results

Tables 4.1 and 4.2 present the current state of the leaderboard, with the most recent results available at huggingface.co/datasets/flowers-team/StickToYourRole. Across most models, the use of Chain-of-Thought (CoT) prompting appears to enhance performance consistently. Additionally, both model family and size have a significant influence on outcomes, with models from the Llama-3 and Qwen-3 families generally achieving higher scores relative to their size. Regarding Stress, many models—especially those using CoT—achieve stress values below 0.2, which is typically considered an acceptable threshold. However, none of the models meet the conventional criteria for acceptable fit on the three CFA metrics (i.e. CFI > 0.90 and RMSEA, SRMR < 0.08). Regarding rank-order stability, several larger models - and notably some smaller Qwen-3 models with CoT - reach values of 0.7 or higher, indicating potential saturation on this metric. Taken together, the results suggest that while rank-order stability may be approaching its ceiling for this suite, the persistent gap in CFA scores points to either remaining space for improving value expression in LLMs or a fundamental limitation in applying human-centric theories, such as Schwartz's, to these models. Recent work (Ye et al. 2025a; Biedma et al. 2024) has begun to explore LLM-specific theories of values, offering promising directions for future research.

Table 4.1: Latest state of Stick to Your Role Leaderboard without CoT prompting. Some models reached higher rank order stability of 0.7, but, regarding validation metrics, a significant gap to acceptable levels (e.g. CFI=0.9) remains.

Model	Ordinal Win Rate (↑)	Cardinal Score (↑)	RO Stability (↑)	Stress (↓)	CFI (↑)	SRMR (↓)	RMSEA (↓)
Qwen2.5-VL-72B-Instruct	0.869	0.773	0.792	0.154	0.702	0.246	0.288
Mistral-Large-Instruct-2407	0.813	0.737	0.764	0.169	0.651	0.310	0.330
Llama-3.1-70B-Instruct	0.775	0.711	0.672	0.177	0.708	0.253	0.280
Llama-3.1-Nemotron-70B-Instruct	0.756	0.702	0.675	0.169	0.673	0.284	0.303
Dracarys2-72B-Instruct	0.753	0.699	0.663	0.185	0.692	0.272	0.293
Nautilus-70B-v0.1	0.749	0.707	0.633	0.181	0.751	0.209	0.231
Llama-3.3-70B-Instruct	0.729	0.674	0.689	0.170	0.587	0.380	0.403
Mistral-Small-3.1-24B-Instruct-2503	0.675	0.647	0.569	0.186	0.687	0.295	0.305
Cydonia-22B-v1.2	0.651	0.647	0.595	0.203	0.638	0.313	0.327
Mistral-Large-Instruct-2411	0.603	0.603	0.526	0.201	0.588	0.329	0.336
Llama-3.1-8B-Instruct	0.557	0.568	0.469	0.212	0.595	0.354	0.361
Ministrations-8B-v1	0.459	0.458	0.322	0.259	0.525	0.447	0.437
Qwen2.5-14B-Instruct-1M	0.454	0.466	0.364	0.240	0.481	0.484	0.481
Qwen2.5-VL-7B-Instruct	0.417	0.427	0.222	0.257	0.559	0.400	0.376
Mistral-Nemo-Instruct-2407	0.387	0.406	0.214	0.258	0.519	0.449	0.420
Mixtral-8x7B-Instruct-v0.1	0.347	0.382	0.215	0.262	0.453	0.503	0.491
Mistral-7B-Instruct-v0.2	0.285	0.321	0.144	0.265	0.380	0.573	0.548
phi-3-medium-128k-instruct	0.282	0.308	0.097	0.265	0.430	0.550	0.538
Llama-3.2-3B-Instruct	0.251	0.307	0.068	0.287	0.482	0.519	0.490
phi-4	0.231	0.295	0.065	0.272	0.412	0.530	0.513
dummy	0.150	0.229	-0.009	0.293	0.376	0.622	0.592
Qwen2.5-VL-3B-Instruct	0.144	0.229	0.021	0.291	0.310	0.648	0.622
Llama-3.2-1B-Instruct	0.143	0.238	0.007	0.293	0.337	0.598	0.566

Table 4.2: Latest state of Stick to Your Role Leaderboard with CoT prompting. Quite a few models reached higher rank order stability of 0.7, but, regarding validation metrics, a significant gap to acceptable levels (e.g. CFI=0.9) remains.

Model	Ordinal Win Rate (↑)	Cardinal Score (↑)	RO Stability (↑)	Stress (↓)	CFI (↑)	SRMR (↓)	RMSEA (↓)
Qwen2.5-VL-72B-Instruct	0.899	0.836	0.813	0.159	0.845	0.100	0.148
Llama-3.1-Nemotron-70B-Instruct	0.823	0.807	0.799	0.156	0.777	0.157	0.205
Llama-3.3-70B-Instruct	0.813	0.783	0.810	0.170	0.705	0.248	0.287
Dracarys2-72B-Instruct	0.791	0.774	0.790	0.158	0.731	0.258	0.279
QWQ-32B	0.767	0.772	0.809	0.177	0.693	0.211	0.307
Mistral-Large-Instruct-2407	0.758	0.787	0.779	0.182	0.776	0.276	0.217
Llama-3.1-70B-Instruct	0.739	0.772	0.763	0.159	0.741	0.207	0.252
Qwen3-32B	0.680	0.749	0.695	0.173	0.688	0.275	0.292
Qwen3-32B-A3B	0.667	0.749	0.695	0.174	0.702	0.275	0.294
Mistral-Large-Instruct-2411	0.656	0.733	0.706	0.172	0.700	0.270	0.297
Nautilus-70B-v0.1	0.642	0.724	0.719	0.169	0.673	0.279	0.308
Qwen3-225B-A22B-FP8	0.612	0.718	0.679	0.181	0.719	0.246	0.262
Qwen3-8B	0.612	0.718	0.719	0.199	0.680	0.299	0.308
Mistral-Small-3.1-24B-Instruct-2503	0.605	0.703	0.685	0.177	0.671	0.297	0.315
Qwen2.5-14B-Instruct-1M	0.588	0.702	0.655	0.179	0.713	0.269	0.269
Qwen3-4B	0.561	0.697	0.660	0.201	0.693	0.270	0.285
Llama-4-Scout-17B-16E-Instruct	0.509	0.618	0.497	0.195	0.698	0.272	0.274
Llama-3.1-8B-Instruct	0.502	0.620	0.554	0.178	0.620	0.347	0.353
GLM-4-32B-0414	0.455	0.592	0.523	0.189	0.589	0.375	0.379
Cydonia-22B-v1.2	0.418	0.566	0.493	0.208	0.562	0.404	0.392
reka-flash-3	0.385	0.490	0.289	0.219	0.636	0.324	0.327
Llama-3.2-3B-Instruct	0.378	0.492	0.310	0.235	0.640	0.367	0.340
Mistral-Nemo-Instruct-2407	0.374	0.524	0.410	0.213	0.565	0.400	0.382
Ministrations-8B-v1	0.339	0.492	0.349	0.230	0.543	0.378	0.378
Mixtral-8x7B-Instruct-v0.1	0.288	0.416	0.281	0.247	0.467	0.522	0.497
Qwen2.5-VL-7B-Instruct	0.259	0.424	0.286	0.259	0.453	0.479	0.464
phi-4	0.218	0.316	0.099	0.251	0.427	0.527	0.515
Llama-3.2-1B-Instruct	0.173	0.285	0.018	0.292	0.457	0.498	0.458
Qwen2.5-VL-3B-Instruct	0.132	0.266	0.060	0.288	0.365	0.601	0.590
Mistral-7B-Instruct-v0.2	0.121	0.234	0.026	0.291	0.329	0.650	0.623
phi-3-medium-128k-instruct	0.116	0.225	-0.009	0.292	0.346	0.623	0.592
dummy	0.114	0.229	-0.009	0.293	0.376	0.622	0.592

4.5 Discussion

This chapter presents a study into the stability of values expressed by Large Language Models. We consider (interpersonal) Rank-Order stability and (intrapersonal) Ipsative stability. We evaluate value stability over different contexts induced by simulating conversations about different topics. We conduct experiments with and without instructing the models to simulate particular personas. Over our experiments, we observed consistent trends of value stability: Mixtral, Mistral, GPT-3.5 and Qwen model families were more stable. These trends are also confirmed on stability of downstream behavior, and in terms of correlation between value expression and downstream behavior. This consistency implies that the robustness of models to unexpected context-based changes can be studied as a property of LLMs. LLMs instructed to simulate personas exhibit much lower than human stability (despite the comparison being skewed in their favor), which further diminishes over longer conversations. This insight highlights the limitation of the studied LLMs and motivates future research on models specialized in simulating coherent populations of individuals. Based on those experiments we construct a leaderboard, which included harder tasks and validation tests.

This chapter highlights how seemingly unrelated context changes can result in unpredictable and unwanted changes in behavior. We argue that the context-dependence, and more precisely, value stability, should be seen as another dimension of LLM comparison alongside knowledge, model size, speed, and similar. Instead of evaluating LLMs with many different questions from a single minimal context, they should also be evaluated with the same questions asked in many different contexts (i.e. in terms of their context-dependence and value stability). This research presents first steps in that direction.

Limitations and Future Work Due to computational requirements for evaluating LLMs, most of our experiments consider only five different conversation topics and rather short conversations (this was extended to nine context-chunks and contexts up to 8000 tokens in the leaderboard). Increasing the number of topics and conversation length further could provide more precise insights into the stability of various models.

Given that most LLMs have primarily been trained on English text, we present contexts and questionnaires in English as well. Extending the experiments to different languages is a necessary step toward adequately understanding the cultural biases in LLMs.

This chapter studied one of the issues with a common practice of directly applying psychological questionnaires to LLMs: the extreme context dependence, which is higher than what one might expect in humans. However, the question under which conditions can different questionnaires be applied to LLM still remains largely open. It is possible that other aspects, in addition to context-dependence, need to be addressed to make stronger claims about the value expression in LLMs.

We believe that this project opens many research avenues regarding context-dependence and value stability of LLMs. Similar questions to those explored in this project could be explored for personality traits, cultural values, cognitive abilities and knowledge. An interesting direction is to explore if the same model can exhibit high stability both in settings with and without the persona instruction, or if specialized models are required. Increasing the LLMs' interpretability could help understand how to increase their stability. This chapter opens a new area of research in creating, evaluating and analyzing models specialized in simulating coherent and diverse populations. Such models are needed for many applications such as replicating human studies (Aher, Arriaga, and Kalai 2022a), simulating social interactions (Park et al. 2023), training teachers (Markel et al. 2023), and many more.

Finally, in this chapter, we focused on Schwartz's theory of values, which is a theory crated for humans. Recently, arguments have been raised that LLM-specific theories might be needed (Hagendorff et al. 2023; Ye et al. 2025a). This emerging field of "machine psychology" offers many exiting new directions.

From psychology - Part 2

In this section, we discuss how we leveraged and adapted social psychology research in Part II. This mostly pertains to research done by Shalom H. Schwartz, and to a lesser extent Geert Hofstede.

Concepts We mainly borrowed concepts from two psychological theories Schwartz's theory of basic personal values (Schwartz 1992a) and Hofstede's theory of cultural values (Hoftede, Hofstede, and Minkov 2010). The values proposed in these theories have been extensively studied in humans, making them a natural starting point for investigating value expression in LLMs From these theories, we borrow not only specific concepts but also the broader approach of characterizing and studying the behavior of an *intelligent* system through a set of distinct constructs. It is possible that a different, LLM specific, set of values could be more suited to study LLMs, and could potentially better predict LLMs behavior and better characterize LLM value expression.

Methodology We borrow the methodology of administering questionnaires to study an intelligent system. For that we reuse the VSM, PVQ and SVS questionnaires associated with the two aforementioned theories. Furthermore, we discuss in detail how one should be careful when directly applying those questionnaire primarily due to broken assumptions - such as context dependence. We adapt the methodology for evaluating value stability - Rank-Order and Ipsative stability - to study the robustness of LLMs to unexpected changes in context. This part provides an example of how a methodology from psychology intended for one purpose, can be adapted to ask different but related questions in AI.

Part III

An evolving culture

5 Recursive Training Loops in LLMs

How training data properties modulate distribution shift in generated data?

What is this chapter about? This chapter focuses on the question "How do cultures composed of AI agents (and humans) change and evolve over time?". We focus on a particular aspect of this question - the increased presence of AI-generated content on social media. This creates feedback loops where subsequent generations of models are trained on previously generated synthetic data. Such loops were shown to lead to *distribution shifts* - models misrepresenting the true underlying distributions of human data (also called *model collapse*). However, it remains poorly understood how human data properties affect such shifts. In this chapter, we provide the first empirical examination of the effect of such properties on the outcome of recursive training. We first confirm that using different human datasets leads to distribution shifts of different magnitudes. Through exhaustive manipulation of dataset properties combined with regression analyses, we identify a set of properties predicting distribution shift magnitudes. Lexical diversity was associated with amplified detrimental shifts, while semantic diversity and data quality with reduced ones. Furthermore, we find that these influences are highly modular: data scrapped from a given internet domain has little influence on the content generated for another domain. Finally, experiments on political bias reveal that human data properties affect whether the initial bias will be amplified or reduced. Overall, our results portray a novel view, where different parts of internet may undergo different types of distribution shift. Future directions could consider more complex social structures or a more active human role. Furthermore, similar questions could be explored *top-down*. For instance, one could organize real-world social media data chronologically and search for patterns corresponding to those observed in the simplified, isolated settings considered in this work. Such research could help us better understand the complex real-world cultural evolution dynamics caused by iterative training feedback loops.

Timeline: Most of the research in discussed in this chapter was done in 2025

Contribution: Most of the research in discussed in this chapter was done in 2025 in shared 1st authorship with Jérémy Perez, who contributed significantly to the conceptualization of the project and conducted the experiments with political bias (Section 5.4.5).

Scientific output: - **Grgur Kovač**[*], Jérémy Perez[*], Rémy Portelas, Peter Ford Dominey, and Pierre-Yves Oudeyer (2025). 'Recursive Training Loops in LLMs: How training data properties modulate distribution shift in generated data?' In: *Proceedings of EMNLP 2025 (Oral).*

[*]Shared 1st authorship.

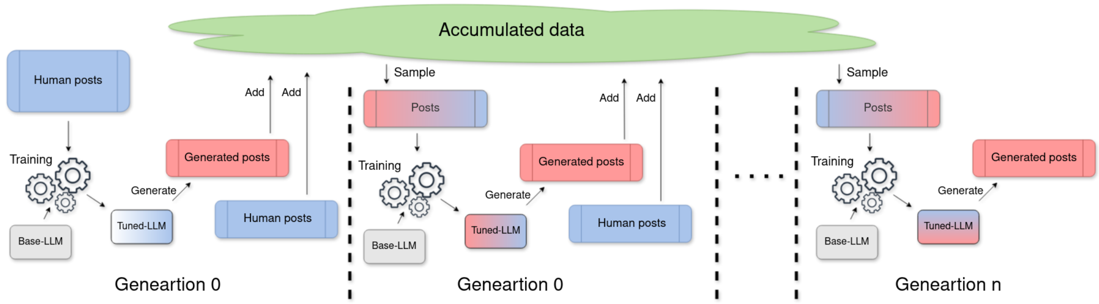


Figure 5.1: Iterative chain. In each generation, a fresh base model is fine-tuned on texts sampled from the Accumulated data pool (except generation 0, where it's trained only on human posts). The model generates posts, which are added to the pool alongside some newly sampled human posts.

5.1 Introduction

Large Language Models (LLMs) are increasingly contributing to the creation of internet content, being used for journalism (Brigham et al. 2024), coding (Jiang et al. 2024b) and generating content on social media (Ferrara et al. 2016). The increasing amount of synthetic, LLM-generated data on the internet introduces a precarious feedback loop: LLMs trained on datasets containing synthetic data will themselves generate data that will be used to train future models. Shumailov et al. 2024a demonstrated that this process, known as **recursive training**, can have detrimental effects, causing models to progressively lose information about the true underlying distributions they are intended to approximate. This results in a gradual change in generated distributions, often accompanied by a reduction in variance. While this has sometimes been described as *model collapse*, we refer to this mismatch between the true and the generated distribution as *distribution shift*, and limit the term collapse to refer to *detrimental* distribution shifts, such as losses in quality or diversity. Such detrimental effects (Guo et al. 2024b) as well as bias amplification (Wang et al. 2024d) have been reported in previous work. Their potential societal consequences make it imperative to better understand the dynamics of recursive training.

Internet data varies along a wide range of properties. For instance, certain domains may be associated with a higher ratio of synthetic-to-human data (e.g. GitHub), others with lower quality data (e.g. Reddit), and some with lower diversity data (e.g. specialized forums) If those properties affects the outcome of recursive fine-tuning, we may expect different types of shifts on different parts of the internet

Given the early stage of research in this field, existing studies often ignore this diversity, relying on simplifying assumptions and focusing on abstracted settings. To the best of our knowledge, how different data properties influence distribution shifts remains largely unexplored, aside from studies examining the ratio of human to synthetic data (Bertrand et al. 2023b; Bohacek and Farid 2023; Kazdan et al. 2024; Martínez et al. 2023b; Zhang et al. 2024b). Filing this gap is therefore crucial to draw a more nuanced and detailed picture of the consequences of recursive fine-tuning.

In this chapter, we adopt the iterative chain paradigm used in previous studies (Shumailov et al. 2024a; Gerstgrasser et al. 2024b). Our experimental setup is shown in Figure 5.1. The process begins with fine-tuning a base LLM on a selection of human data (e.g. Reddit posts). This model generates data, which are added to the pool of Accumulated data together with newly sampled human data. In each subsequent generation, a new base model is fine-tuned on data sampled from the Accumulated data pool. This model, in turn, generates new data, which are again added to the pool along with fresh human data. Compared to the standard iterative chain design where each participant only observes the output of the previous participant, this design follows Gerstgrasser et al. 2024b where data from all participants are accumulated together. We adopt this design as we believe it better captures the real-world dynamics of generated online data (e.g. previously generated AI posts are not removed from social media). This pipeline allows us to study how generated data evolve across successive generations, with a particular focus on the distribution shift from the first to the final generation.

In our experiments, we study how various properties of human data (e.g. quality, diversity, bias) influence the dynamics of distribution shifts in recursive training chains. We use five datasets spanning three domains (Twitter, Reddit and Wikipedia). First, we confirm that the choice of the dataset greatly influences the consequences of iterative fine-tuning (Section 5.4.2): while some datasets exhibit sharp decreases in diversity and quality, others are more robust to such shifts. Our second set of experiments (Sections 5.4.3 and 5.4.4) aims to uncover specifically which which properties of training data mitigate or amplify distribution shifts. Using a variety of clustering techniques we create 200 subsets for each of the four different dataset. We run iterative chain experiments with these clusters, and conduct a series of regression analyses mapping various data properties to the degradation in the quality and diversity of generated texts. We find that lexical diversity is associated with greater degradation, while semantic diversity has the opposite effect. Furthermore, we observe that these influences are highly modular, with generated content being mostly influenced by human data properties from the same domain. This suggests that different internet domains might undergo distinct and relatively independent distribution shifts regardless of models being trained on a mixture of domains. Finally, our last set of experiments focuses on the evolution of political bias. The results indicate that the type of shift observed (bias reduction, amplification or inversion) depends on the political lean of the the human data. This empirically confirms that properties of human data play an important in shaping the outcome of recursive training.

The code for reproducing the simulations, analyses and figures is available on our GitHub*.

The main contributions of this work are:

- We propose and experimentally confirm the hypothesis that different training datasets lead to different distribution shift dynamics, motivating an investigation on the underlying causes
- Through an extensive set of experiments (four datasets over three domains), we outline several data properties as influencing distribution shift dynamics

* https://github.com/flowersteam/ce_llms

- We reveal that these influences are highly modular, with generated content being mostly influenced by human data properties from the same domain.
- We find that distribution shifts also occur in terms of political lean, and that the type of shift (bias amplification, reduction or inversion) depends on the political lean of the human data

5.2 Related Work

Recursive fine-tuning and model collapse A rapidly growing body of literature has focused on the consequences of recursively training generative models on synthetic data (Schaeffer et al. 2025). The phrase "model collapse", coined in Shumailov et al. 2024b, refers to the progressive degradation of models induced by this feedback loop. This phenomenon has been studied both theoretically (Dohmatob, Feng, and Kempe 2024; Dohmatob et al. 2024; Bertrand et al. 2023b; Alemohammad et al. 2023b) and empirically, on both generative image models (Martínez et al. 2023b; Martínez et al. 2023a; Bohacek and Farid 2023; Hataya, Bao, and Arai 2022; Alemohammad et al. 2023b) and language models (Zhang et al. 2024b; Guo et al. 2023; Kazdan et al. 2024; Briesch, Sobania, and Rothlauf 2023; Gerstgrasser et al. 2024c). Theoretical results have provided valuable insights, for instance showing how it is characterized by the disappearance of distribution tails (Dohmatob, Feng, and Kempe 2024; Dohmatob et al. 2024; Shumailov et al. 2024b). Empirical studies have allowed to establish several properties of this phenomenon, such as the role of synthetic-to-real-data ratio (Briesch, Sobania, and Rothlauf 2023; Hataya, Bao, and Arai 2022) or strategies for mitigating collapse (Gerstgrasser et al. 2024c; Kazdan et al. 2024; Zhang et al. 2024b). Recently, Wang et al. 2024e showed that recursive LLM fine-tuning can lead to bias amplification. These works do not systematically evaluate how the properties of the human dataset used in their experiments affect their conclusions. Here, we extend this literature by investigating how those properties impact the outcome of recursive training.

Cultural dynamics in artificial agents The motivation for this research area stems from the observation that human-made technologies have transitioned from passive mediators of cultural evolution (e.g., the printing press) to active generators of cultural content. This shift has been described as the emergence of machine culture - culture mediated or generated by machines (Brinkmann et al. 2023). Understanding the dynamics that shape the evolution of machine-generated content over time is therefore crucial. This has led researchers to study cultural dynamics in populations of reinforcement learning agents (Cook et al. 2024; Schmitt et al. 2018; Team et al. 2021; Prystawski, Arumugam, and Goodman 2023; Nisioti et al. 2022) and of LLMs (Perez et al. 2024b; Perez et al. 2024a; Nisioti et al. 2024; Vallinder and Hughes 2024; Burton et al. 2024). Our work extends this literature by examining the factors that modulate the evolution of LLM-generated content.

5.3 Methods

5.3.1 The iterative chain paradigm

We use the iterative chain paradigm inspired by Shumailov et al. 2024a; Gerstgrasser et al. 2024b. Our experimental design is shown in Figure 5.1. First, a base LLM is fine-tuned on 8000 samples from a human dataset (e.g. Wikipedia articles or Reddit posts). This model generates $4000 * r$ posts, where r is the synthetic-data ratio. Those posts are added to the pool of accumulated data together with $4000 * (1 - r)$ newly sampled human posts. In all subsequent generations, a new base model is fine-tuned on 4000 posts sampled from the accumulated data pool, and $4000 * r$ posts generated by this model are added to the accumulated data pool together with $4000 * (1 - r)$ newly sampled human data. In each generation, a new base model is sampled from four possible options: LLaMa-3.2-1B (Dubey et al. 2024), Qwen2.5-1.5B (Team 2024b), SmolLM-1.7B (Allal et al. 2024), Falcon3-1B-Base (Team 2024a)), and fine-tuned using LoRA (Hu et al. 2021) (see appendix D.2.5 for details). Five seeds were used in all experiments. This pipeline enables to study the evolution of generated data over generations, and most notably, the difference between data generated in the first and last generations.

5.3.2 Datasets

We conducted our experiments on five datasets: two consisting of Twitter posts, two of Reddit posts, and one of Wikipedia paragraphs. These platforms were chosen because they are likely to be increasingly populated with AI-generated content, often indistinguishable from human-written text. Additionally, they are frequently scraped to construct training dataset for language models. Finally, they cover a diverse range of topics and language styles - an essential requirement for investigating the effects of data properties on recursive training dynamics. Refer to Appendix D.2.2 for details.

5.3.3 Metrics

In this work, we study distribution shift dynamics in terms of quality, semantic diversity and political lean. Irrespective of how much content a model outputs (which varies with the synthetic-data ratio), we always evaluate those metrics on a sample of 250 generated texts.

The Semantic Diversity of a set of texts is measured as the pairwise cosine diversity in the stella_en_1.5B_v5 model (Zhang et al. 2024a), as in previous studies (Guo et al. 2024b). **Quality** and **Political lean** are estimated by using LLaMa-3.3-70B-Instruct (Dubey et al. 2024) in the LLM-as-a-Judge setup. The prompt is inspired by Wang et al. 2023 and Chen et al. 2023b, and adapted to our task of evaluating the quality of short texts (see appendix D.2.3 or details and validation of that adaptation). In sections 5.4.3 and 5.4.4, we additionally rely on the following metrics. **Lexical Diversity** is estimated as SelfBLEU (Zhu et al. 2018), computed as the average BLEU score (Papineni et al. 2002) of each text using all other texts as references, following prior work (Guo et al. 2024b). **Gaussianity**

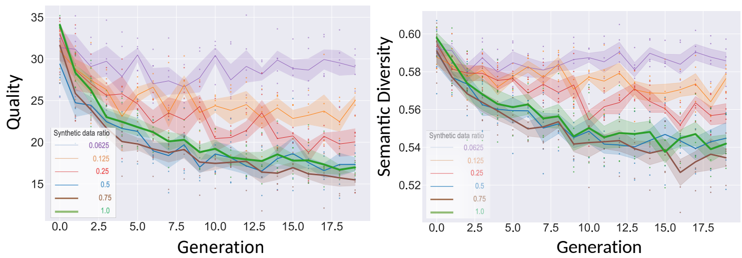


Figure 5.2: Evolution of quality (left) and diversity (right) over generations for different synthetic data ratios on the *100M_tweets* dataset. Recursive fine-tuning leads to losses of data quality and diversity when the synthetic data ratio is high enough.

is measured by fitting a 2D UMAP projection on embeddings from the stella_en_1.5B_v5 model, and computing the AIC (Akaike 1974) of a 2D Gaussian distribution fit to this space. **Positivity** is assessed using the SentimentIntensityAnalyzer tool from NLTK (Hardeniya et al. 2016), which assigns a sentiment score to each text ranging from -1.0 (highly negative) to 1.0 (highly positive).

5.4 Experiments

In this section, we study the following questions:

- Does synthetic data ratio impact distribution shift dynamics?
- Do different datasets exhibit different distribution shifts dynamics?
- Which dataset properties best predict distribution shift dynamics?
- Does training on multiple domains influence distribution shift dynamics?
- Do datasets with different political biases lead to different shifts in political lean?

5.4.1 Does synthetic data ratio impact distribution shift dynamics?

In this experiment, we aim to reproduce the effect of the synthetic data ratio (Briesch, Sobania, and Rothlauf 2023) on the shifts toward lower quality and lower diversity induced by recursive fine-tuning. This ratio corresponds to the proportion between the AI-generated data and the freshly sampled human data that are added to the Accumulated data pool at each generation.

Figure 5.2 shows the evolution of quality and semantic diversity over consecutive generations, where human data comes from the *100M_-tweets* dataset. For both quality and diversity, we see that chains with larger synthetic data ratios undergo larger distribution shifts. Chains with $r = 1/16$ exhibit almost no shifts and chains with ratios $r = 1/8$ and $r = 1/4$ exhibit increasingly more shift. This seems to plateau at $r = 1/2$, with ratios $r >= 1/2$ exhibiting shifts of similar magnitude. This experiment shows that, for the *100M_tweets* dataset, synthetic data ratio has a significant impact on distribution shift dynamics, and that the loss in quality and diversity appears to plateau when half or more training data is synthetic.

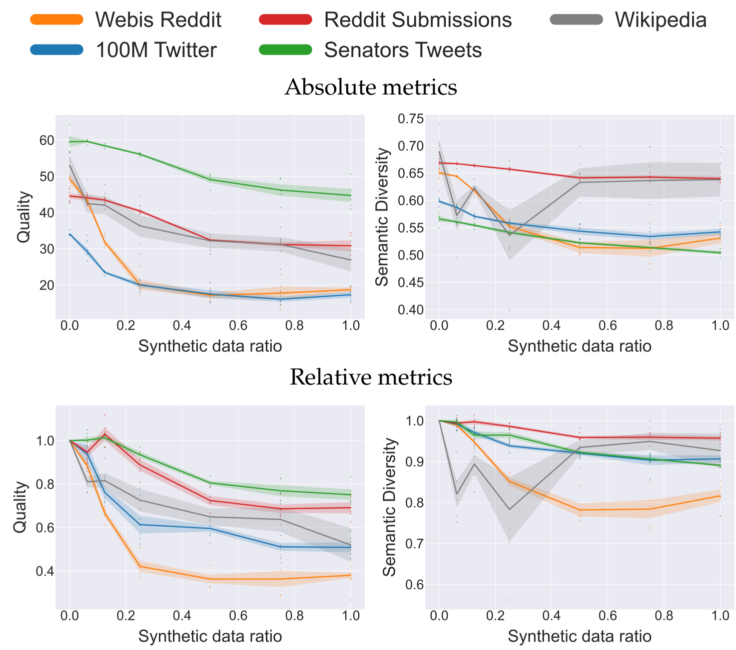


Figure 5.3: Effect of synthetic data ratio on absolute and relative quality (left column) and diversity (right column) at the last generation, in four different datasets. Absolute measures (top row) correspond to the value of the corresponding metric at generation 19. Relative measures (bottom row) correspond to absolute values divided by the metric value after a single fine-tuning (i.e. generation 0). Different datasets lead to different sensitivities to synthetic data ratio, with *100M_tweets* (blue) and *webis_reddit* (orange) exhibiting greater losses in quality and diversity.

5.4.2 Do different datasets exhibit different distribution shifts dynamics

In this experiment, we explore how the distribution shift dynamics vary over different datasets. The experiment is methodologically identical to the one in 5.4.1, but we consider five datasets: *100M_tweets* , *senator_tweets* , *reddit_submissions* , *webis_reddit* , and *wikipedia*.

Figure 5.3 shows the values of the metrics at the end of the iterative chain (i.e. those measured at generation 19 in Figure 5.2) as a function of synthetic data ratio. Figure 5.3 shows both absolute (top) and relative (bottom) quality (left) and diversity (right) scores. *Relative scores* correspond to absolute scores divided by the score of the data generated in generation zero. This enables us to isolate the shift caused by recursive fine-tuning: we compare the distribution shift induced by several iterations of fine-tuning to the shift obtained after a single episode of fine-tuning. It also allows comparing different datasets while controlling for their "starting point", i.e. the value of quality and diversity in the human dataset. Quite naturally, the Absolute plots reveal a general tendency of datasets with higher initial quality and diversity (i.e. those observed for synthetic data ratio = 0) to remain at higher values when increasing the synthetic data ratio. Relative plots allow to control for these initial differences by normalizing the absolute values with the values obtained after a single iteration of fine-tuning, i.e. *relative loss* in quality and diversity. *webis_reddit* exhibits a relative loss both in quality and diversity. *reddit_submissions* and *senator_tweets* datasets exhibit small relative losses in quality and diversity, and *100M_tweets* dataset also exhibits a small relative loss in diversity. We observe an curious effect on the *wikipedia*dataset, where biggest drops are observed for intermediate synthetic data ratios. Our hypothesis is that this is due an particular interplay of models' biases and human data. In appendix D.3.3, we discuss this hypothesis in more detail and conduct a toy experiment to provide further support for this hypothesis. Overall, this experiment reveals that the choice of the dataset

Table 5.1: Regression coefficients for distribution shifts in semantic diversity and quality. Bold values indicate statistical significance. Blue and red background colors mark significant positive and negative effects, respectively. Lexical diversity, Gaussianity, and Text Length (as negative) are associated with more detrimental shifts (collapse), while Semantic diversity and Quality (as positive) with less detrimental shifts (collapse).

Coefficient	All	*webis_reddit*		*100M_tweets*		*reddit_submissions*		*wikipedia*	
Synthetic data ratio		1/8	1/4	1/8	1/4	1/8	1/4	1/8	1/4
Semantic Diversity									
`Semantic diversity`	-0.0007	**0.0075**	0.0117	0.0087	**0.0291**	0.0003	0.0057	0.0152	0.0181
`Lexical diversity`	**-0.0126**	**-0.0155**	**-0.0487**	-0.0012	**-0.0051**	-0.0026	**-0.0098**	**-0.0306**	-0.0091
`Gaussianity`	**-0.0092**	-0.0001	-0.0006	-0.0042	**-0.0121**	0.0016	-0.0025	**-0.0325**	-0.0170
`Quality`	**0.0187**	-0.0003	-0.0021	-0.0006	**0.0105**	0.0027	0.0040	**0.0410**	0.0283
`Positivity`	-0.0031	**-0.0037**	**-0.0071**	0.0007	0.0004	-0.0050	**-0.0153**	-0.0050	**0.0094**
`Text length`	-0.0015	0.0005	0.0114	-0.0015	**-0.0214**	-0.0049	**-0.0154**	-0.0356	**-0.0407**
Quality									
`Semantic diversity`	**0.0105**	**0.0410**	**0.0185**	0.0140	0.0316	0.0129	0.0058	-0.0177	0.0219
`Lexical diversity`	**-0.0603**	**-0.0892**	**-0.0478**	-0.0043	**-0.0275**	0.0080	0.0107	-0.0240	**-0.0719**
`Gaussianity`	**-0.0158**	0.0012	-0.0095	-0.0102	-0.0139	-0.0026	0.0033	-0.0159	-0.0122
`Quality`	**0.0616**	**0.0335**	-0.0018	-0.0044	**0.0547**	0.0113	0.0055	0.0297	**0.1023**
`Positivity`	**0.0074**	-0.0055	**-0.0097**	**0.0304**	**0.0380**	0.0070	**-0.0431**	-0.0073	0.0106
`Text length`	**-0.1327**	**-0.1029**	0.0037	0.0157	**-0.0554**	-0.0244	-0.0181	-0.0414	**-0.1218**

greatly impacts the distribution shifts dynamics.

5.4.3 Which dataset properties best predict distribution shift dynamics?

The previous sections indicates that the extent to which recursive fine-tuning leads to distribution shifts varies greatly between datasets. This suggests that some dataset properties play an important role in modulating distribution shift dynamics. In this section, we describe a series of regression analysis experiments aimed at uncovering which properties have such strong influence on distribution shifts. We focused on six dataset properties as relevant candidates: Semantic diversity (using pairwise cosine diversity), Lexical diversity (using self-BLEU), Gaussianity, Quality, Positivity and Text length (see Appendix D.2.3 for details on how those were selected)). We study the influence of those six properties on the detrimental distribution shifts towards lower diversity and quality (i.e. model collapse).

We extracted 200 clusters from four of the five datasets from the previous section, using the method described in appendix D.2.4 (the *senator_tweets* dataset was excluded due to its insufficient size). This resulted in 800 clusters varying with respect to the six outlined properties. We used those properties as predictors in our regression analysis. For each of these clusters, we ran two iterative chain experiments, respectively with synthetic data ratios 1/4 and 1/8, using the corresponding cluster as the "human data". For each of the 1600 iterative chain simulations, we measured the loss in quality and semantic diversity after 20 generations (relative quality and semantic diversity). We used those values as dependent variables. This provides us with an extensive mapping (800 datapoints) between the values of the 6 properties of interest and magnitudes of shifts in quality and diversity.

By performing regression analyses, we were then able to determine which properties correlate with distribution shifts. We performed nine separate regressions: two for each of the four datasets across two synthetic data ratios (grouping chains from the same dataset and ratio), and one with all

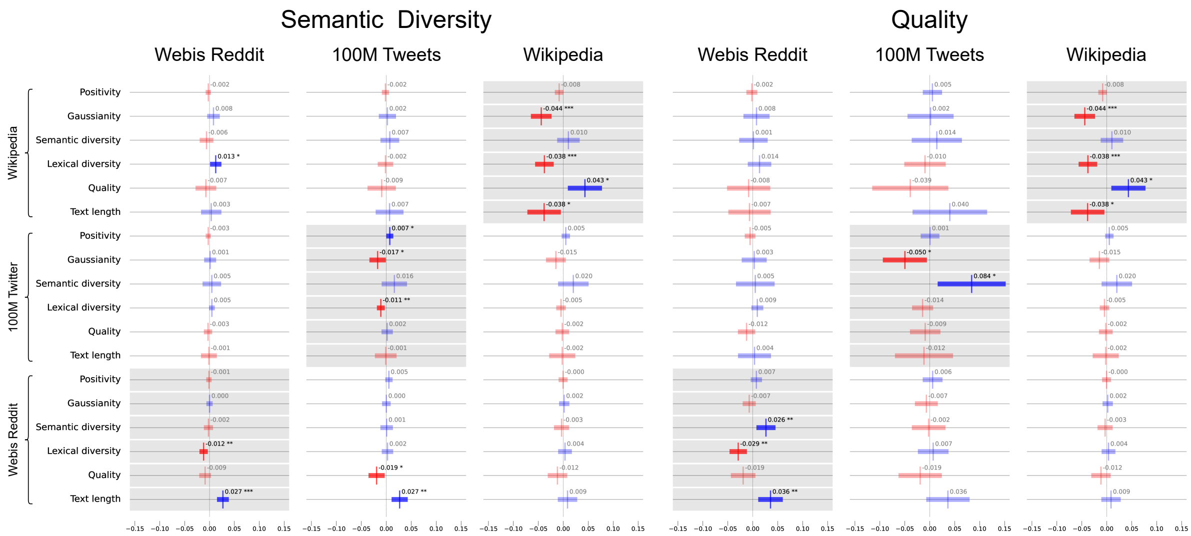


Figure 5.4: Regression coefficients for distribution shifts in semantic diversity and quality in multi-domain experiments. Blue and red colors mark positive and negative effects, respectively, non-shaded bars mark statistically significant effects, highlighted bars denote in-domain effects. Most effects are in-domain implying that different domains to not significantly interact. The in-domain predictors are consistent with those in single domains experiments: semantic diversity and quality (as positive) are associated with more detrimental shifts (collapse), lexical diversity and gaussianity (as negative) with less detrimental shifts (collapse).

datasets and ratios. Table 5.1 show the results, with columns corresponding to different regression analyses. Statistically significant coefficients ($p < 0.05$) are shown in bold. Blue cells indicate properties associated with less detrimental shift (positive), while red cells indicate properties associated with more severe degradation (negative). Regression analyses conducted on all data outlined the following properties as significant. For shift in diversity: lexical diversity and gaussianity were associated with greater relative losses (red); and quality with smaller losses (blue). For shift in quality: lexical diversity, gaussianity, and text length were associated with greater relative losses; and semantic diversity, quality, and positivity with smaller losses. It is interesting to note that lexical and sematic diversity seem to have opposite effect when one would expect them to be correlated. To clarify this is the power of regression analysis that is able to separate various aspects of diversity. This result is intuitively plausible, as lexical diversity that is not accompanied by semantic diversity may reflect surface-level variation—such as the use of synonyms or varied phrasing—without contributing meaningful conceptual richness. Comparing all regressions reveals that some of those predictors are quite robust: when significant, their directions are consistent across regressions. Lexical diversity is the most robust predictor appearing 11 times. Quality and length appear 7 times and often together. Semantic diversity appears 5 times and Gaussianity 4 times. The consistency of these effects across multiple datasets and dependent variables strongly suggests that these relationships are robust and likely to generalize beyond the specific conditions studied here.

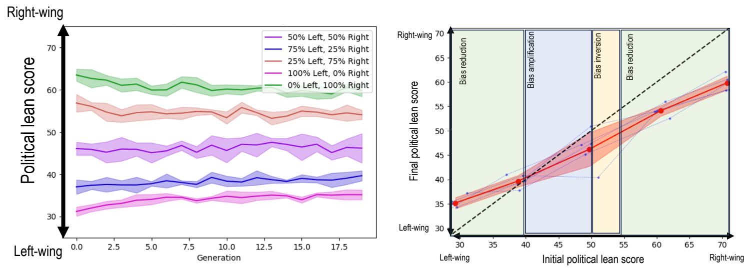
5.4.4 What happens when models are trained on data from multiple domains?

So far we have considered situations in which models are trained on data from a single Internet domain. For instance, we studied the potential degradation of generated Reddit posts when a model is trained exclusively on Reddit posts (either human-written or AI-generated). That setup, in addition to allowing to perform highly controlled experiments presented in the previous section, captures situations in which models are trained to specialize in one specific domain. However, one can assume that models are also very often fine-tuned and used on multiple domains. In this sections, we explore whether training from (and generating content for) multiple domains modifies the relationships between dataset properties and distribution shifts identified in the previous section.

On the one hand, we could expect models trained on data from multiple domains to merge internal representations, and therefore that the properties of content from a given domain (e.g. Reddit) influences the content generated in another domain (e.g. Wikipedia) (*Hypothesis 1*). Alternatively, models may keep the representations of different domains separate, in which case the properties of data in one domain would not influence on the generation in another domain (*Hypothesis 2*). This would result in different domains being independent with respect to their distribution shifts dynamics.

To explore that question, we slightly modified the experimental pipeline from the previous sections. Having already extracted 200 clusters from *wikipedia*, *webis_reddit* and *100M_tweets* datasets, we merge those 600 “pure” clusters into 200 "mixed" clusters so that each “mixed” cluster consists of one “pure” cluster from each dataset (i.e. $mixed_i = wikipedia_i \cup webis\_reddit_i \cup 100M\_tweets_i, i \in [1, 200]$). We then run 200 iterative chain experiments using those clusters. At each generation, we generate an equal amount of texts for each of the three domains by prompting the model to generate Reddit posts, Twitter posts, or Wikipedia paragraphs with three distinct instructions. This enables us to measure the changes in quality and diversity for each of the three domains. We map those changes to the properties of the “pure” clusters constituting each “mixed” cluster. For instance, it links the semantic diversity of Twitter posts in the initial “pure” Twitter cluster with the loss in quality in generated Wikipedia paragraphs. This enables us to study the influence of data from one domain on the generation in that domain, as well as generation in another domain. We performed regression analyses to estimate the effect of 18 predictors (the six properties over three domains) on 6 dependent variables (relative losses in quality and diversity in the three domains).

Figures 5.4 show the results of the aforementioned experiments. Columns correspond to the two dependent variables in three domains. Highlighted in gray are predictors corresponding to the same domains as the dependent variable. We can make two key observations. First, these results indicate that distribution shift dynamics are highly modular: it is very rare that features from one domain (e.g. Reddit) significantly predict distribution shifts in an unrelated domain (e.g. Wikipedia). Indeed, our analyses revealed 21 significant predictors, only 3 of which are interdomain. This would suggest support for *Hypothesis 2*, with different domains undergoing distribution shifts independently from one another. Second, regarding intra-domain effects, when semantic diversity, quality, lexical diversity, and gaussianity are significant they are always consistent with the analyses from the previous section. This consistency



(a) Average political lean

(b) Initial vs Final lean

Figure 5.5: Effect of recursive fine-tuning on political lean. (a) Evolution of political lean over generations, for initial distributions with varying degrees of political polarization. We observe a general tendency for political bias to be reduced over generations. (b) Average political lean at the last generation as a function of political lean in the human data. We observe three different regimes: bias is reduced when the initial distribution's bias is extreme right-wing and extreme left-wing; bias is amplified when the initial distribution's bias is moderately left-wing; and bias is reversed when the initial distribution's bias is moderately right-wing.

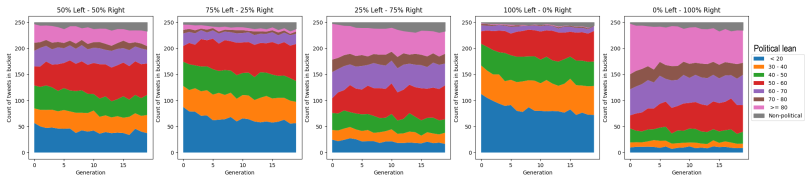


Figure 5.6: Proportion of tweets with different degrees of political bias over generation. We partition the generated tweets in eight bins according to their political lean. The proportion of neutral tweets tends to increase, while the proportions of extreme left and extreme right tweets decrease. The proportions of more nuanced left and right tweets appear to stay the same.

between different training conditions further supports the generality of the uncovered effects.

5.4.5 Political lean

While most works on recursive fine-tuning studied detrimental distribution shifts (e.g. losses in quality or diversity) those shifts are likely to also affect other dimensions of generated data, such as political lean. In this section, we study the distribution shift of political lean as a function of human data lean on the *senator_tweets* dataset.

To manipulate the political lean of the human data, we annotated the political lean of the dataset (as described in section 5.3.3) and split it into left-wing and right wing partitions. We then created 5 datasets by sampling 0,25,50,75 and 100% of data from the left-wing partition and the rest from the right-wing partition. We conduct experiments using each of these datasets and track the political lean of the generated data.

On Figure 5.5a, we observe a progressive shift from the initial political lean towards more neutral content. In Appendix D.3.4, we observe a rise in the proportion of politically neutral tweets, as well as a marginal rise in non-political tweets. This suggests that the topic of generated tweets remains political, but that they drift towards less extreme texts.

Figure 5.5b aims to assess the effect of political lean in human data on the dynamics of political lean shift. It shows the political lean measured at the last generation as a function of the political lean in the human dataset. Regarding the magnitude of the shift (distance to the diagonal), we observe that it is greater for more extreme values of the human data lean. Regarding the direction of the shift, we observe three different regimes: 1) bias is *reduced* when the human distribution's bias is extreme right-wing and extreme left-wing, 2) bias is *amplified* when the initial distribution's bias is moderately left-wing, and 3) bias is *reversed* when the initial distribution's bias is moderately right-wing. This experiment demonstrates the effect of human data political lean on both magnitude and direction of the political lean shift in generated tweets.

In the results presented above, we considered the evolution of the *average* political lean. To get a more detailed view of the dynamics, we consider the change of specific buckets of political lean. On Figure 5.6, we observe that the proportion of neutral tweets tends to increase, and the proportions of extreme left and extreme right tweets tend to decrease. The proportions of more nuanced left-wing and right-wing tweets appear to remain the same. This suggests that the evolution of average political lean reported above may be due to extreme tweets (either left-wing or right-wing) being gradually *replaced* by neutral tweets.

5.5 Discussion

This chapter studies the effect of human data properties on distribution shift dynamics in recursive training loops with large language models (LLMs). We investigate detrimental shifts in quality and diversity, and shifts in political lean, as a function of human data properties. First, we show that distribution shift dynamics vary depending on the human datasets used. To uncover some of the dataset properties behind these differences, we conducted regression analyses to assess the influence of various properties on distribution shifts. This revealed significant and consistent effects: lexical diversity and gaussianity are associated with larger detrimental distribution shifts, while semantic diversity and data quality with reduced ones. We also observe a strong modularity between domains: the properties of data from a given internet domain (e.g. Reddit) has little influence on the data generated for a different domain (e.g. Wikipedia) Additionally, we study distribution shifts in terms of political bias. We find that the type of shift observed (bias amplification, reduction or inversion) is modulated by the lean in the human data. Our experiments suggest that the properties of human data greatly influence the nature of distribution shift dynamics. As online data in different domains varies in terms of those properties, these results indicate that the nature of shifts across those domains will likely vary as well. See Appendix D.1 for a longer discussion. Overall, this chapter highlights the importance of understanding how data properties influence distribution shift dynamics, and thus complements the emerging understanding of the consequences of recursive fine-tuning - an increasingly relevant issue given the growing role of AI in generating online content.

Limitations

The main limitation of this chapter is that the experimental design remains significantly simplified compared to real-world settings. More specifically, recursive fine-tuning happens in networks of LLMs rather than in linear chains, and discrete generations are only an approximation of the continuous interactions that actually take place. Moreover, we considered chains of LLMs without any human intervention. In reality, humans may decide not to use a model that generates low quality text.

Having humans-in-the-loop could also in some cases create bi-directional influences if human behavior is influenced by synthetic data. Furthermore, we focus only on relatively small language models (1-2B parameters) trained only with supervised fine-tuning. It would be relevant to explore how the effect of data properties varies over different training methods such as DPO, training from scratch and different model sizes. Because of the recency of this research area, such simplifications very common in studies of recursive training. Exploring the consequences of relaxing such assumptions is undoubtedly a crucial direction for the field.

Another limitation is that we only considered text in English. Similarly, our experiments with political lean were conducted on exclusively US-politics (tweets for US senators). Studying texts from diverse cultures and languages is a crucial future direction to ensure that our conclusions are representative and general.

Finally, although we attempted to cover a wide set of dataset properties that might affect distributions shift, this set is not exhaustive, and it's highly likely that some metrics we didn't account for are important predictors of distribution shifts.

Ethics Statement

The results we present reveal how the magnitude and direction of shifts in generated content can be modulated by manipulating various features of training datasets. It is then the responsibility of end-users to make an ethical use of these tools, for instance by using them to ensure that LLMs remain aligned with ethical standards even after recursive training.

When LLMs Play the Telephone Game

6

Cumulative Changes and Attractors in Iterated Cultural Transmissions

What is this chapter about? Like the previous chapter, this chapter focuses on the question "How do cultures composed of AI agents (and humans) change and evolve over time?". In contrast to the previous chapter, which examined feedback loops in training LLMs on their own generated data, this chapter focuses on iterated text transformations through repeated interactions of already fine-tuned models. As large language models (LLMs) start interacting with each other and generating an increasing amount of text online, it becomes crucial to better understand how information is transformed as it passes from one LLM to the next. While significant research has examined individual LLM behavior, existing studies have largely overlooked the collective behavior and information distortions arising from iterated LLM interactions. Small biases, negligible at the single output level, risk being amplified in iterated interactions, potentially leading the content to evolve towards attractor states. In a series of telephone game experiments, we apply a transmission chain design borrowed from the human cultural evolution literature: LLM agents iteratively receive, produce, and transmit texts from the previous to the next agent in the chain. By tracking the evolution of text toxicity, positivity, difficulty, and length across transmission chains, we uncover the existence of biases and attractors, and study their dependence on the initial text, the instructions, language model, and model size. For instance, we find that more open-ended instructions lead to stronger attraction effects compared to more constrained tasks. We also find that different text properties display different sensitivity to attraction effects, with toxicity leading to stronger attractors than length. These findings highlight the importance of accounting for multi-step transmission dynamics and represent a first step towards a more comprehensive understanding of LLM cultural dynamics.

Timeline: Most of the research discussed here was conducted from March to October 2024.

Contribution: 2$^{\text{nd}}$ authorship, contribution was primarily in setting up and simulating LLM interactions.

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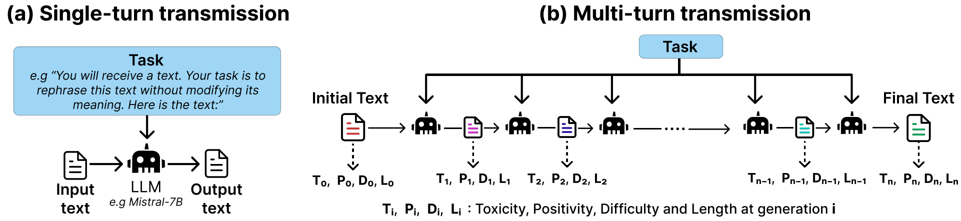
6.1 Introduction

As discussed in Chapter 5, Large language models (LLMs) are playing an increasingly significant role in the production of media content across various domains (Brinkmann et al. 2023). Numerous researchers have studied the properties of LLM-generated content in particular their biases, for instance, with respect to gender (Acerbi and Stubbersfield 2023),



(a) Single-turn transmission: an LLM receives a human-generated input text (e.g. a story) and a task (e.g. "rephrase the text") and generates an output text. (b) Multi-turn transmission: a chain of LLMs is given the same task, with the first LLM receiving an initial text and subsequent LLMs receiving the output of the preceding LLM. Measures of *toxicity*, *positivity*, *difficulty*, and *length* are recorded at each step of the chain.

Figure 6.1: The transmission chain experimental design.

values (Atari et al. 2023), politics (Motoki, Pinho Neto, and Rodrigues 2023), and so on. They were also found to generate at least as attractive (Marlow and Wood 2021) texts as humans and to display similar cognitive biases (Echterhoff et al. 2024).

As the share of AI-generated content increases, previously generated content will influence future generators. This can take two forms. First, AI-generated content will be used as training data for new LLMs, which is what we explored in the previous chapter. Second, which we explore in this chapter, LLMs directly interact with other LLMs or AI generated content. For instance, LLMs are increasingly being used in multi-agent settings (Zarzà et al. 2023; Park et al. 2023; Park et al. 2022; Xiao, Yin, and Shan 2023; Hua et al. 2023; Vezhnevets et al. 2023; Chuang et al. 2023) and are already interacting with other chatbots on social media *. While *single-turn behaviors* of LLMs prompted with a *human-generated prompt* are under active investigation, little is known about the effect of iterated multi-turn interactions. Many unknowns remain about how populations of LLMs might self-organize, as other complex systems do. Research in complex systems traditionally studies how global-level patterns emerge from local interactions (Gleick and Hilborn 1988; Mitchell 2009). Here, we ask whether multi-turn behaviors conditioned on LLM-generated content cause the appearance of new kinds of biases, undetectable in single-turn behaviors but accumulating across iterated interactions of LLMs.

To address this question, we again take inspiration from the cultural evolution literature and in particular from a research tradition called *cultural attraction theory* (CAT) (Sperber 1985; Morin 2016; Miton 2024). CAT aims to determine how non-random transformations of cultural information during transmission events may lead to the evolution of progressively more stable forms, referred to as *attractors*. Although the precise conceptualization of attractors varies across authors, an encompassing definition may be *"theoretical posits that capture the way in which certain ideational variants are more likely to be the outcome of transformations than others."* (Buskell 2017). Importantly, the existence of attractors would predict that for a broad range of starting conditions, different variants of a given cultural trait will converge towards the same attractor, that is, to a cultural trait that possesses specific properties.

As in the previous chapter we borrow the transmission chain design where

* https://chirper.ai/

chains of participants receive, produce and transmit social information from and to each other in a sequential manner (as in the popular *telephone game*). This powerful and highly controlled design allows to evaluate the high-level patterns that emerge from the accumulation of directional changes during single-turn transmission events.

We conducted several transmission chain experiments with LLMs, where the first LLM-based agent in the chain receives a human-generated text, elaborates on it, and then passes it to the next agent in the chain. This transmission step is repeated with different instances of the LLM agent until the end of the chain is reached (see Figure 6.1). This iterative chain design is simpler compared to the one in the previous chapter. Here, each agent receives only the output of the previous agent, while in the previous chapter it was a set sampled from a mix of all previously generated text and human data.

In our experiments, we simulated repeated transmission to observe the direction in which text properties evolve, starting from a broad range of initial values. We study the evolution of various text properties, namely its *toxicity*, *positivity*, *difficulty*, and *length*. We measure the effect of a single interaction compared to 20 consecutive interactions, and demonstrate that single-turn interactions are usually not enough to predict multi-turn dynamics. For instance, on E.11 (toxicity - take inspiration) we see that at first Mistral appears less toxic at the first iteration, but after 9 generations Llama3-8B ends up being much less toxic. One may therefore choose Mistral-7B based on single-step evaluation, even though Llama3-8B is the optimal choice for many applications. By comparing the properties of the initial (human-generated) and final texts (after several transmissions between LLMs), we illustrate and study the existence of potential attractors in LLM cultural evolution and estimate their strength and position. We conduct our analyses on five different models (ChatGPT-3.5-turbo-0125, Llama3-8B-Instruct, Mistral-7B-Instruct-v0.2, Llama3-70B-Instruct, and Mixtral-8x7B-Instruct-v0.1), three different tasks (i.e. instructions to either "rephrase", "take inspiration from", or "continue" the initial text) and 20 different initial texts. Although our focus is on a better understanding of the cultural dynamics of LLMs, the metrics and evaluation methods introduced here may also be of interest to researchers studying human cultural evolution.

Our main contributions in this chapter are:

- We propose that there might be a gap in current LLM evaluations methods (single-turn evaluations might not be suited to assess the properties of multi-turn interactions)
- We empirically confirm this hypothesis by showing that multi-turn interactions indeed often lead to distributions of text properties that are significantly different from what is observed after a single interaction (Appendix E.2.1)
- We introduce novel conceptual and methodological tools to fill this gap, grounded in research in cultural evolution, and in particular the concept of cultural attractor (Section E.1.3).
- We showcase the potential of this method by applying it to compare the effect of different tasks, of different models, of temperature, and of fine-tuning on the properties of multi-turn interactions. (Section 6.2.2).

- We find several robust effects, such as the fact that less constrained tasks lead to stronger attractors, that some properties posses stronger attractors than others, and that fine-tuning can shift the position and modify the strength of attractors.

6.2 Results

For each of the 6 models, 3 tasks, and 20 initial texts, we ran 5 transmission chains with 50 transmission steps. In the main experiment, each chain is composed of a population of agents sharing the same underlying model. In an additional experiment, we also studied chains where different models interact with one another (Appendix E.2.4). We provide some examples of generated texts in Appendix Section E.1, and complete data on the companion website †. By extracting the properties of generated texts at each generation of each chain, we can study the evolution of these properties through generations, measure how they are affected by interactions beyond single-turn effects, as well as detect and characterize theoretical attractors.

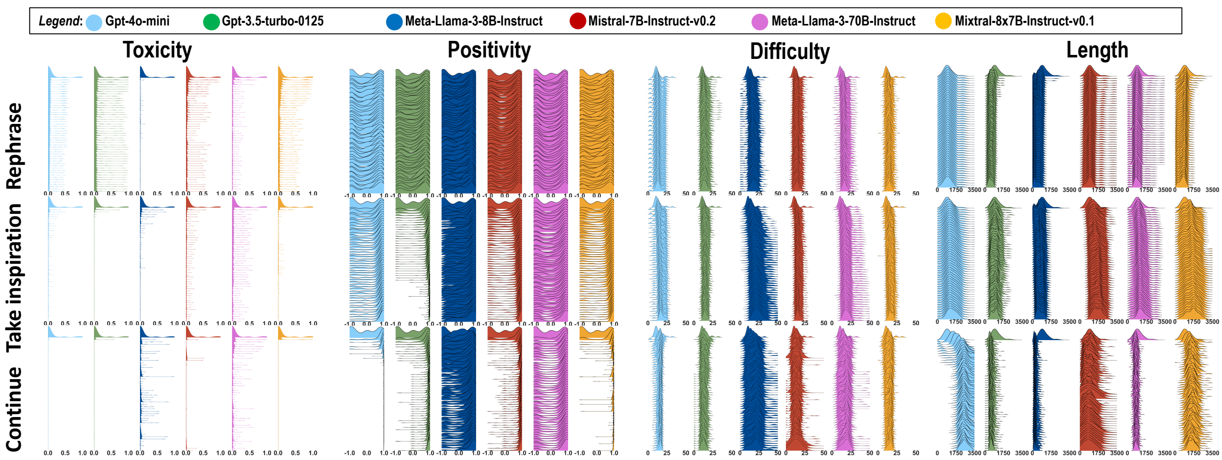


Figure 6.2: Evolution of the distribution of text properties across generations. We here represent the distribution of each of the four properties at each generation, for each model and task. These distributions thus represent the properties observed in the set of 100 transmission chains (20 initial texts * 5 seeds) for each model and task. For each property, task and model, the 50 generations are arranged vertically, with first generations at the top and last generations at the bottom.

6.2.1 Qualitative analysis of property evolutions over generations

In Figure 6.2, we show the evolution of property distributions over generation for each model and task. This reveals important difference depending on the analyzed property, the task and the model. For instance, we observe that *toxicity* converges very quickly to a very narrow peak centered around 0. This is very different from the evolution of *positivity*, for which the initial distribution appears to be quite preserved for the *Rephrase* task (Figure 6.2, first row), while less constrained tasks such as *Take inspiration* (second row) and *Continue* (third row) lead to more visible changes. Interestingly, we observe that for Llama3-8B and Llama3-70B,

† https://sites.google.com/view/llms-play-telephone

the distribution of *positivity* values converges to a bimodal distribution, while distributions are unimodal for other models. In some cases, we also observe that different models lead the distributions to be shifted in opposite directions. For instance when looking at the evolution of texts *length*, using GPT3.5 or Llama3-8B leads text to become on average shorter, while using Mixtral-8x7B or GPT-4o-mini shifts the distribution towards greater lengths.

6.2.2 What influences the presence, strength, and position of attractors?

Effect of model, task and property Visual inspection of the evolution of text properties as presented on Figure 6.2 indicate that multi-turn transmissions lead distributions to become skewed toward certain values, which suggests the presence of attractors. The task assigned to a chain and the model type populating it appear to influence the position of those attractors, as well as their strength (i.e. how quickly do shifts in distributions happen). To have quantitative measures of attractors strengths and positions, we use the method described in E.1.3 and Figure E.1. Figure 6.3 presents the estimated strengths and positions of attractors, and fitted linear regressions are provided as supplementary material in Figure E.4. For all combinations of property, task and model, we found that the recurrent relationship defined by the fitted linear regression converges. This means that all conditions admit a theoretical attractor as defined in Section E.1.3. To better disentangle the respective contributions of model type, task and property on attractors position and strength, we fitted Bayesian models predicting attractor **Strength** as a function of **Task**, **Model** and **Property**, and predicting attractor **Position** as a function of **Task** and **Model**, for each of the four considered properties. We use 95% Credible Intervals (CI) to assess significance. Those confidence intervals,as well as details of statistical models, are provided in Appendix section E.2.

We find a strong effect of **Task** on attractor strength: *Continue* leads to significantly stronger attraction than *Take Inspiration* , itself leading to significantly stronger attraction than *Rephrase* . This supports our observation that less constrained tasks lead to stronger attraction than more constrained tasks. To specifically test this hypothesis, we conducted additional experiments manipulating only the room for variation allowed in the task, which confirmed this hypothesis (Figure E.7).

Different properties are also found to display different sensitivity to attraction effects. We detect that *toxicity* possesses significantly stronger attractors than *positivity*, *difficulty* and *length*. As for the effect of model, we observe significantly weaker attraction for Llama3-70b compared to GPT3.5, Llama3-8B and Mixtral-8x7b. GPT-4o-mini also displayed significantly weaker attractors than GPT3.5, Llama3-8B and Mixtral-8x7b.

As for the position of the attractors, we found that the position of the attractor for *positivity* was significantly lower for Llama3-8b than for GPT3.5, GPT-4o-mini, Mistral-7b and Mixtral-8x7b, and that the task *Take inspiration* and *Continue* both led to significantly higher *positivity* than the *Rephrase* task.

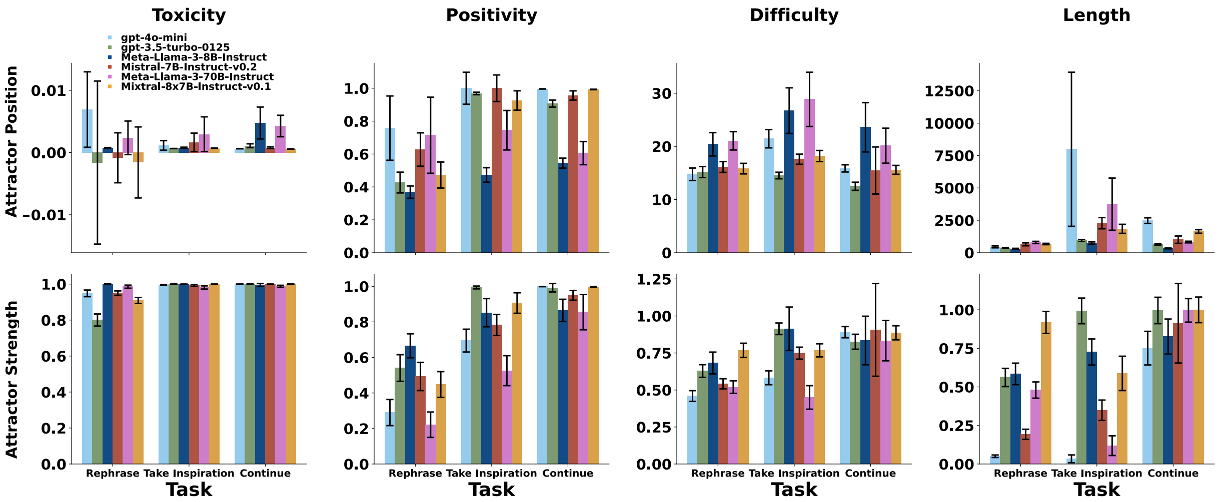


Figure 6.3: Attractors strength and position. The height of the bars represent the position (top row) and strength (bottom row) of theoretical attractors estimated using the method described in Section E.1.3, for each property (columns), task, and model. Less constrained tasks, such as *Continue*, appear to produce stronger attractors than more constrained tasks, such as *Rephrase*. Attractors appear to be stronger for *toxicity* than for *length*. Finally, we can notice that the position of attractors appears to vary between models.

6.3 Discussion

While current studies analyzing the outputs of LLMs are restricted to a single prompt-output interaction, we borrowed the methodology from studies on human cultural evolution to address how cultural content may evolve over transmission chains with LLMs. This resulted in a series of *telephone game* experiments assessing the evolution of cultural content in LLMs as a function of models, instructions, and text properties. Our results reveal that several changes in generated content appear after multiple iterations. For example, we observed that the *difficulty* of a provided text was preserved after an LLM was prompted to elaborate it a single time, but changed dramatically after the text was processed iteratively by a chain of LLMs. Those qualitative observations were confirmed by statistical tests (see Appendix Section E.2.1), where we found that multi-turn interactions lead the distributions of text properties to become significantly different distributions obtained after single-turn interactions.

By comparing the properties of input texts to those of texts produced by transmission chains spanning several generations of LLMs, we identified property-specific patterns in the convergence of LLM dynamics toward attractor states, and we propose a method to estimate the strength and positions of those attractors. Using this method, we found that some properties (e.g. *toxicity*) display quicker convergence rates toward attractors, and that the position of these attractors varies between models. Moreover, our results reveal that more open-ended tasks (e.g. *Continue*) lead to quicker convergence toward attractors than more constrained tasks (e.g. *Rephrase*).

More generally, our results reveal that knowing the output of LLMs after a single interaction is insufficient to predict their behavior in long-term social interactions. Therefore, this suggests that existing training and evaluation methods are not suited to align the behavior of LLMs in multi-step settings. The concepts of attractor position and strength may offer a way to take into account the consequence of multi-turn interactions when comparing and evaluating LLMs.

Limitations and future work The nature of this study required us to make several simplifications that could be explored in future work. One simplification was that we focused on homogeneous transmission chains where all models received the same instructions. Hence, it would be interesting to explore setups with heterogeneous populations of LLMs prompted with diverse instructions. Furthermore, we focused on linear transmission chains, while real-world interactions typically involve networks of senders and receivers. Following some initial endeavors (Nisioti et al. 2022; Perez et al. 2024c), future work may consider the role of network size and structure on attractor dynamics. Similarly, our study could also be extended to hybrid networks consisting of both humans and LLMs interact. Overall, this field remains in its early stages, and many foundational assumptions, such as those discussed above, still need to be critically examined. Expanding beyond these initial constraints will be essential to develop a more comprehensive understanding of how AI systems interact, participate in and reshape cultural transmission over time.

From human sciences - Part 3

In this section, we discuss how we leveraged and adapted cultural evolution research for AI.

Concepts The foundational idea that population-level dynamics cannot be captured through single-step setups was motivated by the same view in the field of cultural evolution. The scientific question explored in this chapter was heavily inspired by analogous questions in that field - namely, how cultural artifacts (such as social media posts) evolve over time as a result of repeated transmission (such as through iterative training).

Methodology We deploy the iterative chain design, a method widely used in cultural evolution research. Given our interest in the evolution of AI-generated content on social media platforms, we manipulate variables such as the ratio of synthetic to human data and various properties of the human data. Addressing these questions requires running a large number of simulations—something that is generally infeasible in studies involving human participants. This part of the thesis demonstrates how a methodological approach from psychology can be effectively repurposed to study analogous questions in AI, and even leveraged more extensively, due to the ability to conduct simulations at a much larger scale.

Part IV

Discussion

7 Discussion

In this final chapter, we summarize the main contributions of the thesis and outline perspectives for future research.

7.1 Summary

This thesis explores the broad question of how insights from social psychology, and more generally human sciences, can be used to evaluate, understand, and build artificial intelligence systems. This overarching question was approached through three distinct facets, each associated with a specific scientific question examined in a separate part of the thesis. These questions are inherently broad and complex, and our aim was not to offer definitive answers, but rather to take initial steps toward addressing them. The structure of the following summary mirrors that of the thesis, discussing each of the three questions sequentially.

How can we evaluate and build AI systems capable of *entering* an existing human culture, i.e. learning from, improving, and teaching a surrounding culture? In Part I (Chapter 2), we leverage developmental theories to outline some of the most basic concepts and abilities relevant for a system to enter an existing culture. More precisely, following the developmental theory of Michael Tomasello, we focus on three aspects of sociality, and from each we outline concepts we deem most relevant for AI at the moment: 1) regarding social cognition: the ability to infer what others see and to engage in joint attention, 2) regarding communication: the development of referential communication through pointing and the beginnings of conventionalized communication through simple language, and 3) regarding cultural learning: imitation and role reversal imitation. In addition, we outline two concepts from Jerome Bruner's theory: formats and scaffolding. Formats refer to the way in which social interactions are structured and presented, while scaffolding refers to the temporary support provided by a caretaker to help a learner achieve a task that would be otherwise too difficult. Then, we present The SocialAI School - a tool to foster research those topics by facilitating procedural environment generation. SocialAI environments can be used with classical multi-modal RL agents, but they can also be instantiated as text worlds to study LLMs. We then present a series of case studies demonstrating the usage of SocialAI to study the outlined concepts and abilities with RL agents as well as with LLMs. Our experiments demonstrated the diversity of studies that can be conducted with the SocialAI school, highlighted the limitations of standard RL agents, and showed that while large language models exhibit behavior to an extent consistent with correctly inferring social cues, a performance gap remains - one whose size appears to depend on the problem at hand. This motivates and facilitates future research into building socially competent interactive agents capable of entering a surrounding human culture.

How can we characterize and evaluate socio-cultural aspects of AI systems? In Part II, we focused on value expression as one particular aspect of cultural expression. In particular, we studied the limitations of directly using psychological questionnaires with LLMs, and adapted psychological methodology to evaluate the stability of basic personal value expression in LLM-simulated populations over different contexts. In Chapter 3, we present a positioning where LLM are seen as superpositions of perspectives - rather than exhibiting a persona, a culture, or a set of values, LLMs' behavior is always conditioned on the context (perspective). That is to say providing a context (e.g. a Wikipedia article) collapses the superposition of perspectives into a single perspective (e.g. the perspective of the writer of the article). We show that asking the same questions through different textual formats leads to drastic changes in the LLMs' answers. This implies that we should be weary of making general conclusions from minimal context evaluations. In Chapter 4, we leverage that psychological methodology for estimating value stability to study a more focused question: the stability of LLMs' simulated personas and populations, and provide an systematic set of experiments where we compare LLMs based on their robustness to context changes. In those experiments, we observed consistent trends of value stability: Mixtral, Mistral, GPT-3.5 and Qwen model families were more stable. These trends are also confirmed on downstream behavioral tasks. LLMs studied in this chapter exhibited much lower than human stability (despite the comparison being skewed in the humans favor), which further diminished over longer conversations. This insight highlights the limitation of the studied LLMs and motivates future research on models specialized in simulating coherent populations of individuals. Based on those experiments we construct a leaderboard, which included harder tasks and validation tests. Since it's creation we evaluated many different models on the leaderboard. The leaderboard results imply the benefit of using CoT prompting, and more generally, they suggest that while rank-order stability may be approaching its ceiling, the persistent gap in CFA validation scores points to either remaining space for improving value expression in LLMs or a fundamental limitation in applying human-centric theories, such as Schwartz's, to these models. Very recent work (Ye et al. 2025a; Biedma et al. 2024) has already begun to explore LLM-specific theories of values. Such approaches have the potential to greatly increase our understanding of the inner working of LLMs.

How do cultures composed of AI agents (and humans) change and evolve over time? As AI systems become increasingly integrated into human culture, numerous questions emerge regarding the dynamics of human–AI cultural evolution. For instance, next generations of LLM are trained on current internet data, which includes AI generated content. This creates a precarious feedback loop of new models being trained on synthetic data, which was shown to lead to the degradation of generated context quality. A particularly relevant aspect of the internet are social media, which are likely to be increasingly populated with AI-generated content (often indistinguishable from human-written text) and they are frequently scraped to construct training dataset for language models. For this reason, in Part III (Chapter 5), we study the evolution of generated social media content over iterative transmissions. Specifically, we focused on how various human data properties might influence the evolution of generated data. We fine-tuned language models on a mix of human-written posts and outputs from earlier generations of LLMs, simulating iterative cultural transmission. Through a series of regression analyses, we examined how various properties of the human data influence shifts in the distribution of generated content. For example, we found that higher lexical diversity and greater gaussianity in human data were associated with increased deterioration over generations, while higher semantic diversity and overall data quality with smaller deterioration. We also observed modularity between domains: the properties of data from a given internet domain (e.g. Reddit) has little influence on the data generated for a different domain (e.g. Wikipedia). Additionally, we study distribution shifts in terms of political bias. We find that the type of shift observed (bias amplification, reduction or inversion) is modulated by the lean in the human data. These results imply that, different parts of the internet (containing data of different properties) might exhibit different degradation dynamics.

7.2 Perspectives

In this section we discuss the perspectives opened by this research. As the previous section, this section mirrors the thesis structure in sequentially discussing the three previously outlines scientific questions.

How can we evaluate and build AI systems capable of *entering* an existing human culture, i.e. learning from, improving, and teaching a surrounding culture?

The work presented in Part I represents only an initial step toward the broader goal of developing socially competent AI systems capable of entering and participating in human culture. As such there are several limitations and avenues of future work. Here we will discuss avenues relating to enriching and extending the SocialAI environments, problems, and experimental settings, avenues relating to building more socially competent agents to solve those more challenging tasks, and avenues relating to extending the current set of explored developmental concepts.

A limitation of current SocialAI environments is the simplicity of current social interactions, which are scripted and use a templated language. The advancements in LLMs (majority of which happened after this project ended) could enable enriching SocialAI environments with richer and more naturalistic social interactions, and even simulating artificial populations (similarly to Zhou et al. (2023)). Scripted peers could be replaced with LLM-based agents which could communicate in natural language, give a variety of direct or indirect social cues. This could enable a larger diversity and complexity of social games such as collaboration, competition, discussion, etc.

Another limitation is of current SocialAI environments is that they are all gridworlds. As such they are encoded either as a semantic grid (for RL agents) or a simple textual descriptions (for LLM-based agents), which constitutes a very limited subset of all the possible observation spaces that can be used with interactive agents. Future extensions could include adapting SocialAI environments for use with image-based inputs to enable experimentation with vision-language models (VLMs), or even extending them into 3D settings or real-world settings. Given the recent introduction of LLMs into robotics (Zeng et al. 2023), we could imagine recreating SocialAI tasks and studying concepts outlined in this chapter with physical robots, which could interact with other robots or humans. One particularly interesting direction pertains to the ability to use and understand pantomime - another key concept under the umbrella of referential communication in Tomasello's theory. For instance, an LLM-controlled robot could be instructed to communicate to another LLM-agent to open the blue box without using words. Would LLMs discover the pointing gesture? Could they invent a novel pantomiming gesture to be understood by another LLM or a human? Alternatively, LLMs could be allowed to use language but not use keywords such as ("blue", "box", "open", ...), i.e. verbal pantomime. These are examples of another richer and less constrained way to study referential communication extending our current tasks with pointing, color naming, and hot-cold games. Such directions would enable the study of sociality in AI, that is both strongly grounded in psychology and considering very natural and realistic interactions.

Another set of future work avenues relates to the research of how to build more socially competent agents. This relates to both context of classical reinforcement learning (RL) agents and large language model (LLM)-based agents.

The current RL experiments in the SocialAI school use only standard RL agents, with simple count based intrinsic rewards (which in our pilot studies outperformed classic rewards such as RND (Burda et al. 2018) or RIDE (Raileanu and Rocktäschel 2020)). In the context of traditional RL agents, many fundamental challenges remain unresolved. Open questions include how to design architectural biases, intrinsic motivation mechanisms, and automatic curriculum learning strategies that specifically target the development of the socio-cognitive abilities discussed in this thesis as well as wider range of psychological concepts and developmental theories not discussed here.

An alternative approach to developing socially capable agents involves leveraging LLMs as interactive agents. This can be done either by using an LLM directly as the agent - as in our own work - or by incorporating LLMs as components within more complex architectures, such as those designed for population-based learning (Colas et al. 2023) or reinforcement learning (Pourcel et al. 2024). First, even within the existing set of SocialAI scenarios, several tasks remain unexplored in the context of LLM-based agents. Notably, scenarios involving role reversal and imitation have yet to be investigated. Evaluating LLM agents on these tasks would constitute a natural and direct extension of the present work. Among the tasks that have been explored—such as those requiring inference from linguistic cues—we have observed significant improvements between earlier and more recent generations of LLMs however a gap still remains with expert performance. While these results are promising, they remain preliminary. Drawing stronger conclusions will require more comprehensive evaluations across a wider variety of scenarios and environmental settings.

Finally, while SocialAI already addresses a wide set of socio-cognitive abilities, it still remains focused on a subset of early developmental skills inspired by Tomasello's work. Many important concepts related to later stages of development remain unexplored. One example of an interesting concept is rational imitation, in which children reproduce an observed outcome but adapt the means based on the context. For instance, if an adult with their hands occupied presses a button using their foot, children press the button with their hand. In contrast, children are also known to engage in over-imitation, reproducing irrelevant actions even when they are not required for the outcome. It would be interesting to study how AI agents might balance rational imitation and over-imitation, and how this would compare to animals, children, and adults. Beyond imitation, future research could also explore more abstract and culturally significant constructs, such as norms, fairness, justice, and the role of narrative understanding in human development. The questions of how an AI might learn human norms and notions of justice and fairness are intricately connected to field of AI alignment, which among other things, studies how to create AI systems that to not act in harmful ways (Shen et al. 2023). Similarly, concepts pertaining to other theoretical frameworks, remain unexplored as well. Some notable examples of such developmental theories include those of Erik Erikson (Erikson 1993), Alison Gopnik (Gopnik and Meltzoff 1997), or Cecilia Heyes (Heyes 2019). These concepts are central to social behavior and cognition and would provide fertile ground for evaluating the depth of social understanding in AI systems.

More broadly, many existing studies on the social intelligence in AI remain either not explicitly grounded in psychological theories (Guo et al. 2024a; Chen et al. 2024) or focused on the false-belief aspect of Theory-of-Mind (ToM), which constitutes but a narrow aspect of social intelligence (Ma et al. 2023; Sarıtaş, Tezören, and Durmazkeser 2025; Wang et al. 2025). Moreover, most ToM tasks are presented in static third-person scenarios which diverge from the most practical uses in which agents act in the world (Riemer et al. 2024). While these studies offer valuable contributions and remain highly relevant to the current research community, we believe that they could be significantly enriched through a deeper integration of psychological theory. The framework proposed in Chapter 2 exemplifies how such theoretical grounding can serve as a blueprint and guide research in a more structured and interpretable way. We believe that similar approaches could provide more structured paths to evaluating and building socio-cognitive artificial agents.

How can we characterize and evaluate socio-cultural aspects of AI systems?

Much of the current research on LLM evaluation remains focused on performance-based metrics—typically asking whether a model possesses a particular ability or knowledge (Hagendorff et al. 2023). This paradigm is often aimed at comparing and ranking different models. However, a new perspective is beginning to emerge under labels such as Machine Psychology (Hagendorff et al. 2023) and LLM Psychometrics (Ye et al. 2025b). This shift echoes a historical transition in psychology: from a behaviorist focus on observable actions to the cognitive revolution of the

1950s, which introduced internal mental models and explanatory theories (Miller 2003). Just as cognitive theories enabled psychologists to explain, characterize, and predict a wider range of human behaviors, theoretical frameworks may play a similar role in advancing our understanding of LLMs. An instructive analogy can be drawn from the psychology of human values. The development of robust theories of values—defining core concepts and their latent structure—has allowed researchers to describe individuals and groups in low-dimensional psychological spaces that meaningfully correlate with complex, high-dimensional behaviors. Such theories provide compact representations that help explain and predict social dynamics. A natural first step in studying LLMs, then, is to borrow from psychological theories designed to characterize human minds. However, it is likely that entirely new theories—or at least a re-weighting of concepts to reflect the distinct nature of LLMs—will eventually be required. Our work in Part II illustrates this direction by focusing on context sensitivity as a central organizing property of LLM behavior. Unlike task-specific abilities such as question answering or code generation, context sensitivity is a property that indirectly shapes behavior in many downstream settings. This highlights how certain abstract traits may be more informative than raw performance in understanding the general behavior of these models.

This theoretical perspective opens up exciting opportunities for discovering new latent dimensions that govern LLM behavior. One possible approach would involve evaluating a wide range of LLMs across many behavioral tasks, then applying dimensionality reduction techniques such as principal component analysis (PCA) to uncover underlying structure. This mirrors the historical discovery of personality traits, including the widely used Big Five model (Kabigting 2021). As with the development of value theories in human psychology (see Section Section 1.2), building a robust conceptual framework for LLMs is likely to be a long, incremental process. Very recent work has begun to take concrete steps in this direction, proposing a five-factor value framework that, according to their analysis, better captures the value structure of LLMs than existing human-centric models such as Schwartz's theory (Ye et al. 2025a). These developments highlight the potential of psychometric-style approaches—grounded in both empirical evaluation and theoretical insight—as a promising path toward understanding, comparing, and ultimately shaping the behavior of large language models. Similarly, Yax, Oudeyer, and Palminteri 2024 propose to extract phylogenetic trees of LLMs which can be used to predict benchmark performance. The question of how to characterize LLM's value expression and behavior are very relevant for the field of AI alignment, which studies how to ensure that AI systems act in accordance with human societal norms and values (Shen et al. 2023). Such research has the potential to provide us with frameworks to better characterize and understand LLMs behavior.

Another widely explored approach to characterizing the nature of LLMs involves analyzing their internal activations and representations—commonly referred to as mechanistic interpretability (Zhao et al. 2024). A promising direction for future research lies in bridging this line of work with the aforementioned *cognitive* phenomena. For example, it would be valuable to identify specific neural circuits or activation patterns associated with properties such as context sensitivity or the expression of particular value dimensions. Such mechanistic insights could provide a deeper, model-internal understanding of the cognitive-like traits observed at the behavioral level.

Finally, we conclude by narrowing the focus to our approach in Part II, where we investigated sensitivity to context change as a core property of LLMs. An important limitation is that we focus only on the English language. It is crucial to study value expression in LLMs not only by simulating non-western personas, but also by using the languages associated with non-western cultures. That is because a western-view of some persona (which might be encoded in English text), can be very different from the view of the same persona in their culture. Another limitation of our analysis is that it was confined to a specific setting - value expression within simulated populations - the same question of context-dependence can be easily extended to a wider range of LLM behaviors such as knowledge expression, cognitive abilities, other aspects of culture (cultural values, beliefs, norms, ...), and the manifestation of social or cognitive biases. Most existing benchmarks evaluate LLMs by posing many questions from a single, minimal context. A valuable extension would be to systematically vary the surrounding context and assess whether the model's behavior remains stable or shifts accordingly. This would introduce an additional axis of evaluation - context sensitivity - that could be largely orthogonal to performance on the primary task. Such an analysis could help practitioners make more informed decisions when selecting models for specific applications, which is particularly important in high-stakes or socially sensitive domains.

How do cultures composed of AI agents (and humans) change and evolve over time?

This question can be approached from two complementary directions: bottom-up and top-down. In Part III of this thesis, we adopted the *bottom-up* approach. We design a series of simplified isolated experiments aiming to uncover clear and reproducible principles, such as the role of various data properties on the degradation of generated data. This methodological choice requires various assumptions that abstract away from the complexities of the real-world. More specifically, real world LLM-based systems interact in networks rather than in linear chains, and discrete generations are only an approximation of the continuous interactions that actually take place, i.e. they are deployed in intervals which overlap. Furthermore, we considered only the simplest form of interactions: training on generated text and simple tasks such as rephrasing, summarizing and continuing the text. Much more complex interactions remain to be explored such as negotiation, collaboration, competition, discussion and so on. Moreover, we considered chains where human influence is simplified - human data is simply added to the simulation. In the real world, human agency plays a central role: users and institutions selectively deploy certain models over others, and human-generated content itself may evolve in response to the increasing presence of AI-generated text. Studies with active human participants are needed to better study those questions. Relaxing each of the assumptions outlined in this paragraph constitutes an interesting and relevant direction for further research, which could bring us closer to better approximating the dynamics in the real world.

A *top-down* approach could complement this work by analyzing real-world internet data to either validate patterns observed in controlled experiments or reveal new trends. For example, our results suggest that datasets with high semantic diversity and quality tend to experience smaller declines in overall quality and diversity during training iterations, whereas high lexical diversity correlates with greater degradation. Analyzing internet-scale data from before and after the widespread adoption of LLMs could test whether such patterns are reflected in naturalistic settings. Convergent findings across both paradigms would lend strong empirical support to our hypotheses and deepen our understanding of large-scale cultural feedback loops.

It is also important to highlight the limitation that we only considered text in English and in our experiments with politics focused on exclusively US-politics. Studying texts from diverse cultures and languages is a crucial future direction to ensure that our conclusions are representative and general.

More broadly, the influx of generative AI into human cultural systems is a novel and rapidly unfolding phenomenon. This raises many pertinent questions to explore. Will generative AI amplify polarization, misinformation, or the spread of harmful biases-and under what conditions? How can such outcomes be identified and mitigated? Will the internet continue to serve as a rich and diverse repository of human knowledge, or devolve into a self-reinforcing loop of low-quality, synthetic content? Those questions are also relevant for the field of AI alignment, which includes research on how to mitigate bias and stereotypes (Shen et al. 2023). These are not only pressing research challenges but also central questions for public policy, ethics, and collective decision-making. A systematic, interdisciplinary effort is needed to chart the long-term consequences of human–AI co-evolution and to design safeguards that preserve the richness, integrity, and epistemic value of human culture.

7.3 Conclusion

This thesis explored how theories and methods from psychology and human sciences can inform the design, evaluation, and understanding of artificial intelligence systems. We investigated three key facets of this question:

What does an intelligent system need to enter a human culture? Drawing from developmental theories by Michael Tomasello and Jerome Bruner, we outlined core socio-cognitive abilities most pertinent for current AI research. To support research in this area, we introduced The SocialAI School - tool a to foster evaluating and developing these abilities in artificial agents. Do demonstrate various usages of the SocialAI School we conduct experiments with RL and LLM-based agents. We observe limitations of standard RL agents especially in terms of generalization to new contexts, and that while LLMs exhibit behavior to an extent consistent with correctly inferring social cues, a performance gap remains. This gap also depends on the problem at hand.

How can we characterize a culture encoded within an artificial system, such as a large language model (LLM)? Here we discussed how LLMs exhibit high context-dependence. We leveraged social psychology theories such as Schwartz's theory of basic personal values, and associated methodological tools to evaluate and compare LLMs based on the stability of values expressed by simulated personas. We show that LLMs exhibit strong context dependence and argue for caution when using psychological questionnaires for LLMs. We systematically compare LLMs based their sensitivity to trivial context changes, i.e. on the stability of values expressed by simulated personas over trivial context changes. We observe that some model families - Qwen, Mixtral, Mistral, GPT-3.5 - consistently exhibited higher stability in various experimental setups. Then, then we construct a leaderboard by further extending the methodology. The recent indicate that, in particular when used with CoT, rank-order stability may be approaching its ceiling for this suite, but a persistent gap in CFA validation scores points to either remaining room for improving value expression in LLMs or a fundamental limitation in applying human-centric theories to LLMs.

How does a human–AI culture change and evolve over time? We adapted experimental methods from the field of cultural evolution, particularly the iterative chains design. Through controlled simulations, we explored how different properties of human data influence the evolution of AI-generated content. We found that higher lexical diversity and greater gaussianity in human data were associated with increased deterioration over generations, while higher semantic diversity and overall data quality with smaller deterioration. We also observe that data properties from one domain had little influence on the data generated for another domain. These results suggest that different parts of the internet may exhibit distinct evolutionary dynamics, driven by variations in their underlying data properties.

The three discussed questions are inherently complex and interdisciplinary, and this thesis represents only a first step toward addressing them. Nonetheless, the work opens numerous avenues for future research: from scaling up experimental evaluations of socio-cognitive abilities, to developing new cognitive theories tailored specifically to LLMs, to investigating the dynamics of human–AI cultural feedback in naturalistic settings, and much more. As advanced AI systems become increasingly embedded in human culture, understanding their socio-cognitive capacities, internal representations, and cultural impact becomes not only a scientific challenge but a societal imperative. We hope this thesis offers some modest but meaningful contributions towards this growing field of inquiry.

Part V

Appendix

A Supplementary - The SocialAI School

A.1 Supplementary Material

A.1.1 Architecture of the RL agent

In this work, we use a PPO (Schulman et al. 2017) with an architecture initially designed for the BabyAI benchmark (Chevalier-Boisvert et al. 2019). The policy design was improved in a follow-up paper by (Hui et al. 2020) (more precisely, we extend their *original_endpool_res* model). See Figure A.1 for a visualization of the complete architecture. First, symbolic pixel grid observations are fed into two convolutional layers (LeCun et al. 1989; Krizhevsky, Sutskever, and Hinton 2012) (3x3 filter, stride and padding set to 1), while dialogue inputs are processed using a Gated Recurrent Unit layer (Chung et al. 2015). The resulting image and language embeddings are combined using two FiLM attention layers (Perez et al. 2017). Max pooling is performed on the resulting combined embedding before being fed into an LSTM (Hochreiter and Schmidhuber 1997) with a 128D memory vector. The LSTM embedding is then used as input for the navigation action head, which is a two-layered fully-connected network with tanh activations and has an 6D output (i.e. 5 navigation actions and no_op action).

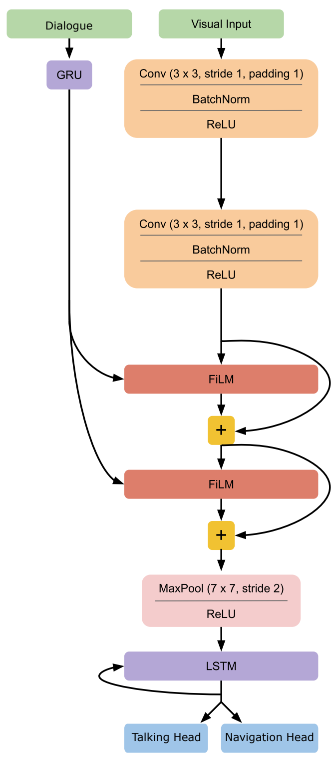


Figure A.1: Our Multi-Headed PPO baseline DRL agent. Architecture visualization is a modified version of the one made by Hui et al. 2020. We perform two modifications: 1) Instead of fixed instruction inputs our model is fed with NPC's language outputs (if the agent is near an NPC), and 2) We add a language action head, as our agent can both navigate and talk.

In order for our agent to be able to both move and talk, we add to this architecture a talking action head, which is composed of three subheads. All of them are consist of two fully-connected layers with tanh activations, and take the LSTM's embedding as input. The first one is used as a switch: it has a one-dimensional output to choose whether the agent talks (output > 0.5) or not (output < 0.5). If the agent talks, the two other networks are used to sample the template and the word. Grammar of the templated language is depicted in table A.1 and examples of multi-modal actions in table A.2.

Note that the textual input given to the agent consists of the full dialogue history as we found it works better compared to giving only the current utterance.

A.1.2 Exploration bonuses

The exploration bonuses we use are inspired by recent works in intrinsically motivated exploration (Pathak et al. 2017; Savinov et al. 2018; Tang et al. 2017). These intrinsic rewards estimate the novelty of the currently observed state and add the novelty based bonus to the extrinsic reward.

We present two techniques for computing the count-based exploration bonus. Both of our count-based exploration bonuses are episodic - they estimate the diversity of states observed within an episode, and assume that beneficial episodes are those with more diverse observations.

Language-based exploration bonus (CBL) For some utterance s_{lang} observed at state s, we count how many times was this utterance observed during the episode. We compute the bonus for this step using the following equation:

$$r_{intr} = T * tanh\left(\frac{C}{(N(s_{lang}) + 1)^M}\right) \tag{A.1}$$

, where M, C, and T are hyperparameters and $N(s_{lang})$ is the number of times the utterance s_{lang} was observed during this episode so far.

Vision-based intrinsic reward (CB) We reward the agent for observing diverse encodings. An encoding is the 6D representation of a cell (see Figure 2.7 for more details). A visual observation consists of 47 (7x7) encodings representing cells in front of the agent. For some visual observation s_{viz} at step s, a set of encountered unique encodings is created (duplicates are removed) $U(s_{viz})$, and then the reward computed using the following equation:

$$r_{intr} = T * tanh\left(\sum_{e \in U(s_{viz})} \frac{C}{(N(e) + 1)^M}\right) \tag{A.2}$$

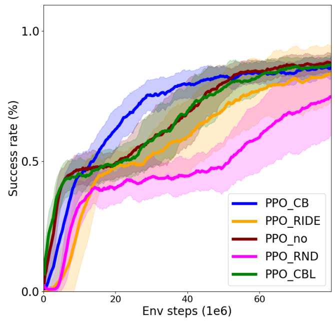
, where M, C, and T are hyperparameters, $U(s)$ is a set of unique encodings visible in state s, and $N(e)$ is the number of times an encoding e was encountered in the current episode.

A.1.3 Pilot experiments

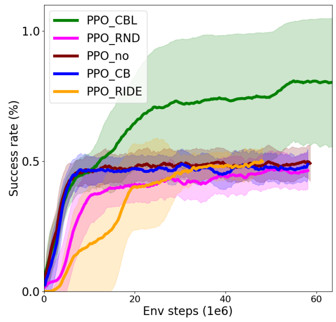
In this pilot experiment, we compare two exploration bonuses presented in section A.1.2 to RIDE (Raileanu and Rocktäschel 2020), RND (Burda et al. 2018), and to the agent without any exploration bonus. * We encoded the peer in a way which used the mix of egocentric and allocentric vision - the peer's gaze and pointing direction were encoded in terms of absolute direction ("NSEW"). We decided to change this to fully egocentric as we found it more natural with regards to the question of socio-cognitive artificial intelligence. We believe that the best performing baselines would also perform best with purely egocentric encodings (the one we use in the rest of the project). For that reason, and to avoid unnecessary energy spending, we do not compare with other baselines on the purely egocentric encoding.

Figure A.2 compares PPO agents trained with different exploration bonuses discussed in section A.1.2 on two different InformationSeeking type environments. The first environment involves the peer pointing to the correct object. Figure A.2b shows that the best performing agent is the one levering the visual count-based exploration bonus (PPO_CB). The second environment involves the peer uttering the color of the correct object. Figure A.2a shows that the best performing agent is the one levering the linguistic count-based exploration bonus (PPO_CBL). We conclude that PPO_CBL is the most suitable baseline for environments involving linguistic cues, and PPO_CB for the other environments.

* We verify our implementation of RIDE and RND by recreating the results of those baselines on environments from (Raileanu and Rocktäschel 2020).



(a) Pilot experiments with the peer pointing to the correct object.



(b) Pilot experiments with the peer uttering the color of the correct object.

Figure A.2: Pilot experiments showing that our count-based exploration bonuses outperform other baselines. On the environments with the pointing gesture, visual count-based ("CB") exploration bonus is the best performing condition. On the environments with utterances, linguistic count-based ("CBL") exploration bonus is the best performing condition.

A.1.4 Adversarial environment type

In the main text we discussed two environment types: InformationSeeking and Collaboration. In this section we explain an additional environment type - Adversarial type. This environment type is used to study the ability of the agent to infer the peer's field of view. An apple will be present in the environment right away. However, the agent will get rewarded only if it eats it while not being observed by the peer (the peer is adversarial). Therefore, the agent needs to infer the right moment to eat the apple. There is one important parameter in this environment type. It refers to the amount of obstacles present in the environment. Figure A.7 shows this environment type without any obstacles (figure A.7a) and with obstacles present (figure A.7b).

A.1.5 Details on the parameters used

The Pointing experiment parameters

The parameter trees used in this experiment are depicted in Figure A.14. We used the InformationSeeking environment type described in section 2.4.3. The Introductory_sequence is set to Eye_Contact, and the Cue_Type to Pointing - the peer will point to the correct object after eye contact. The agent is trained on the following five problems: Boxes, Switches, Levers, Marble, Generators, and on the asocial version of the Doors problem (a version without the distractor or peer). Training on this asocial version is important as it enables the agent to learn how to use a door, which is needed to evaluate generalization.

Role reversal imitation parameters

The parameter trees used in this experiment are depicted in Figure A.15. We used the Collaboration type environments described in section 2.4.3. We evaluate agents on role A of the MarblePass task - the agent has to push the marble to the right side of the environment, from where the peer can push it to the *marble generator*.

Scaffolding parameters

The parameter trees used in this experiment are depicted in Figure A.16. In this experiment, we use the Information seeking environment type with the language feedback cue type. We train agents on all six problems, using different values of the Introductory_sequence and Help parameters. We evaluate the agents on all six problems, with the most complex introductory sequence - Ask_Eye_contact.

The agent denoted by "scaf_4" is trained on four different values of the introductory sequence parameter, and with the Help parameter set to N (the peer will provide cues). This agent will be trained on a total of 18 different environments: six problems, and four introductory sequences. The second agent (denoted by "scaf_8") is also trained on all values of the Introductory_sequence parameter, but it is in addition trained on both values of the Help parameter (N and Y) - a total of 36 environments. In half of those environments (with Help set to Y) the peer will provide the apple to the agent after the introduction (e.g. it will go to the correct box, and open it). In the other half (with Help set to N), the peer will only provide linguistic feedback cues.

In this experiment, we use the PPO agent without an exploration bonus.

A.1.6 Additional case studies

Inferring the meaning of linguistic cues

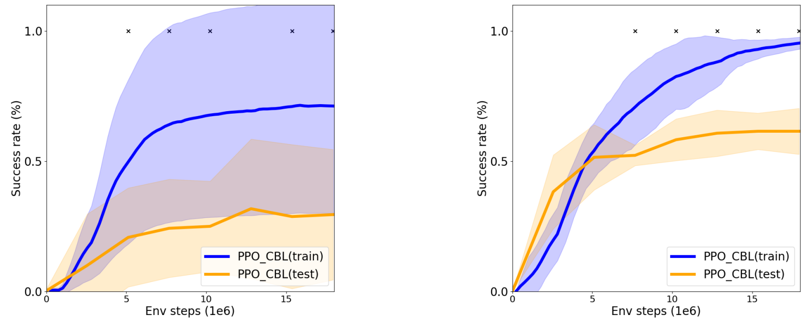
In this section, we study the ability of the agent to infer the meaning of simple words. We follow the same procedure as in section 2.5.2. This case study is motivated by the experiments from cognitive science discussed in section 4. In Carpenter, Nagell, and Tomasello 1998 infants' word understanding steadily increased in the period between 9 and 15 months after birth. We study the following questions:

- Can an RL agent learn to interpret simple utterances?
- Can the agent generalize to new situations, and infer the meaning of those utterances for objects in a new context?

The best performing agent on the linguistic environments in the pilot study was the one using the linguistic count-based exploration bonus (PPO-CBL) (see Appendix A.1.3). We use this agent to address both questions.

Environments The environments are the same as those in section 2.5.2: the Information_seeking environment type, with the introductory_sequence set to Eye_contact. The only difference is that the peer will give linguistic cues instead of pointing. We run two experiments with two different types of linguistic cues: *Color* and *Feedback*. In *Color* the peer will utter the color of the correct object. In *Feedback* the peer will utter a description of how close the agent is to the correct object: "Cold", "Medium", "Warm", and "Hot" meaning, respectively, "far", "medium", "close" and "right next to you". The experimental procedure is the same as the one in section 2.5.2. The agent is trained on the same five problems and the asocial version of the Doors problem.

Figure A.3: The linguistic cues experiments. We study if an RL agent is able to infer the meaning of linguistic cues in order to use the correct object. We consider two types of cues: *language feedback* and *color*. In both settings, the agent was trained on five different problems, and on the asocial version of the Doors problem (only one door and no peer present in the environment) - denoted by "train". Agents were periodically evaluated on the social version of the Doors problem (two doors and a peer giving cues) - denoted by "test". The figure compares the success rate (mean +/- std over 8 seeds) on the training environments with the evaluation on the testing environment. The cross marks depict statistical significance ($p = 0.05$). In both cases the agents achieve much better performance on the training problems, but fail to generalize to a new problem - the agent is not able to infer the meaning of an utterance in a new context.



(a) Language Feedback cue type experiments: the peer gives cues regarding the proximity of the agent is to the correct object (e.g. Hot, Warm, Cold).

(b) Language Color cue type experiments: the peer utters the color of the correct object.

Can RL agents learn to interpret simple utterances?

Figures A.3a and A.3b show the performance of the agent with the linguistic count-based exploration bonus (denoted PPO_CBL_train). We can see that the agent (PPO-CBL) solves these environments efficiently, reaching a final performance of 95.9% and 71.4% for Color and Feedback cue types, respectively. We further analyze the performance of each separate seed for the agent trained on the Feedback cue type. This is shown in Figure A.4 where it is visible that the agent is normally able to achieve high performance, but that there are two seeds which, due to instability, reach a success rate of 0. This experiment shows that the agent is capable of learning to infer the meaning of simple utterances in familiar contexts.

Can the agent generalize to new situations? A more interesting question is whether that agent can infer the meaning of the same word based on a new context. Therefore, we evaluate the agent's generalization abilities in a new scenario - the door problem - following the same procedure as in section 2.5.2. This kind of generalization is particularly interesting as communication depends on our ability to ground words in *new* social contexts: inferring meaning by combining the convention associated to a word with the recursively inferred intention of the speaker. For example, while "red" can mean "open the red box" in one context, it can mean "push the marble towards the red generator" in another.

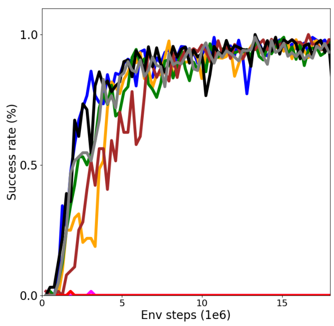


Figure A.4: Per-seed performance on the training environments of the agent from Figure A.3a ("PPO_CBL(train)"). The Figure shows that the agent is able to solve the training tasks efficiently, but that there are two unstable seeds which result in the success rate of 0%.

Figures A.3b and A.3a show the performance of the same agent evaluated on the doors problem (denoted "PPO_CBL_test") They show that neither of the agents is capable of such generalization, which is consistent with the experiments with the pointing gesture in section 2.5.2.

These results motivate future research on what kind of biases could be built into the agents (and in what way) so that they could infer the meaning of familiar words in new contexts. For example, an interesting avenue of future work is to try to combine an agent with a large language models, and see if the knowledge contained in it could make the agent generalize better.

Joint Attention

Tomasello describes joint attention as consisting of two parts: triangulation and recursiveness (Tomasello 2019). He argues that joint attention plays a key role in the 9-month revolution by transforming dyadic interactions (e.g. mimicking facial expressions) to triadic (e.g. imitating an action on an object). Joint attention was also required in the previous experiments (sections 2.5.2 and A.1.6). The agent and the peer triangulated on an external referent, however, the agent could assume that the peer was participating in the interaction.

In this experiment, we aim to conduct a more thorough test of the second aspect of joint attention - *recursiveness* (both participants being aware that they are both sharing attention). To solve the task, the agent needs to infer if the peer is participating and is aware that the agent is participating too. We create environments where the peer, in addition to giving regular cues inside joint attention, gives *misleading* cues outside joint attention. These cues are implemented uttering a random cue, and are given before the agent completes the introductory sequence. In other words, the agent should learn to discriminate between cues given for the agent during joint attention (after the introduction) and cues given regardless of the agent outside joint attention (before the introduction).

We study the following question:

- Can RL agents learn to differentiate between cues given inside and outside joint attention, i.e. can they learn to infer whether the peer is participating in the interaction?

Environments In this section, we extend the environment from section A.1.6 studying the Color cue type. The environment is extended so that the agent must also recursively infer whether the cue is intended for the agent. This misleading cue is given before the introductory sequence is completed, and takes the form of the peer uttering a color of a random one of the two objects. Apart from that, the experiments are conducted in the same way as in section A.1.6 (we train on the same problems for and use the same baseline).

Results Figure A.5 compares the performance (success rate) of the agent trained on this extended environment (denoted by JA) with the agent trained on the regular environment (from the experiment in section A.1.6). These results show that the agent is not able to differentiate between cues given inside and outside of joint attention. We believe that this is due to the cues being highly misleading in this environment. As the peer utters the color of a random object present in the environment 50% of the a misleading cue will be the same as the helpful one.

These results open many avenues for future research. One might study which kinds of biases can be integrated into the agent to make such cues less misleading. The generalization abilities of those agents should also be investigated. For instance, we could study if an agent that learned to ignore misleading linguistic cues would ignore misleading pointing cues.

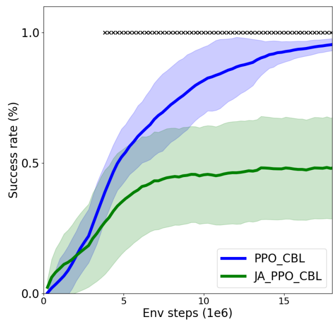


Figure A.5: The joint attention experiment. The environments feature a test for recursiveness - infer if the peer knows that they are working together. The environments are same as the ones from Figure A.3b, but with the addition of misleading cues - random cues given regardless of the agent (a random color). The peer gives misleading cues outside of joint attention (before the introductory sequence). The agent should ignore these cues, and use only cues given inside joint attention. The figure compares the success rate (mean +- std over 8 seeds) of the agent trained on the environments with both regular and misleading cues("JA_PPO_CBL"), to the agent trained on the environments with only regular cues ("PPO_CBL(train)" from figure A.3b). The figure shows that the agent is unable to master the Joint Attention variant.

Imitation learning

In the following section, we study the ability of the agent to learn how to obtain the apple by imitating the peer. This experiment is motivated by an experiment from (Carpenter, Nagell, and Tomasello 1998) discussed in Section 4. In it, infants showed a steady increase in imitation learning abilities in the period between 9 and 15 months after birth. We want to test the agent's ability to imitate an instrumental action on an object.

From an AI perspective, this can be seen as meta-imitation learning. We want to see if an agent can obtain (through gradients) the imitation learning mechanism, which it could then use (during the episode) to learn how to use a new object. In this section, we study the following question:

- Can RL agents learn (through gradients) an imitation mechanism?

In these experiment, we use the agent with the visual count-based exploration bonus (CB), as we found it worked best in our pilot study (see Appendix A.1.3). We compare three agents trained with the same exploration bonus scaled by different weights: 0.25, 0.5, and 1.

Environment The Environment is an Information seeking type environment without a distractor. After the introductory sequence (Eye_contact), the peer will demonstrate using an object to obtain the apple. For example, it will toggle a box or push a generator. Then the peer will then eat the apple, and revert the environment to its initial state. The agent should then imitate the peer - use the same action on the object - to obtain the apple for itself. If the agent uses the object it in the wrong way (e.g. pushes the box instead of toggling it) it will be blocked and the apple will not be obtainable in this episode. The agents are evaluated on a new problem in which the agent encounters a new object for the first time. This means that the agent must pay attention to how the peer uses the object, and use it in the same way. [†]

The agents are trained on five problems (all expect Doors). Most importantly, compared to the experiments in sections 2.5.2 and A.1.6, these agents will not be trained on the asocial version of the Doors problem. That is because, in the generalization testing, we want to see if the agent can learn to use a completely new object.

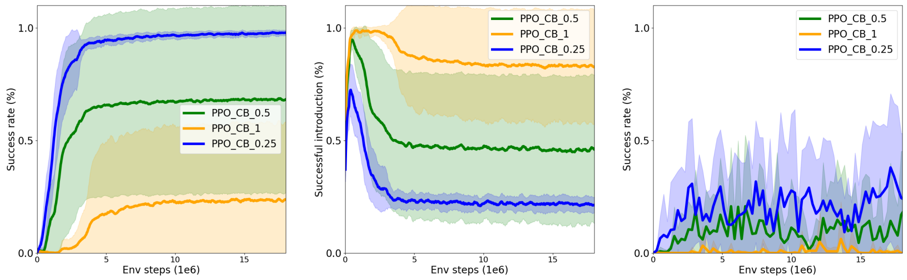
Results Figure A.6 shows the performance (success rate) of the agents on the training environments, the percentage of successful introduction with the peer, and the evaluation on the (unseen) Doors problem.

On figures A.6a and A.6b we can see that the agent with a lot of exploration bonus (PPO_CB_1) is too focused on the peer and, and is unable to solve the task. This is implied by the high percentage of the successful introductory sequence, and low success rate on the training environments. On the other hand the agent with smaller exploration bonus weight (PPO_CB_0.25) solves these environments without problems, however it does use the peer. As such the agent can solve the training environments by ignoring the peer and discovering how to use each object by itself. However, this agent is not able to generalize to a new object as the only way to know how to use that object is to observe the peer's demonstration

[†] The encoding of the peer includes the peer's previous timestep action.

(see Figure A.6c). Figure A.6c shows the performance of those agents on the testing environment. The figure shows that neither of the three agents is capable of acquiring an meta-imitation learning mechanism that can generalize to a novel object.

These results are not surprising, as current exploration bonuses are not well suited to enable RL agents to meta-learn mechanisms. These results imply that an interesting avenue of research is to study how to endow agents with such meta-imitation learning mechanisms that would enable them to learn a behavior in a new scenario. An promising solution to this problem are large language models and other large transformer-based networks pretrained on many other tasks. It would be interesting to study if such agents already have an imitation learning mechanism which would enable such online imitation. This would open up countless avenues of research into various forms of online imitation and emulation learning.



(a) Imitation experiments performance (success rate) on the training environments. **(b)** The percentage of successful introductory sequences on the training environments. **(c)** Imitation experiments performance (success rate) on the testing environment.

Figure A.6: Imitation learning experiments. The peer demonstrates how to use an object (after the agent successfully introduces itself). The agent is trained on five different problems and evaluated on a new problem with a previously unobserved object (a door). A socially proficient agent should be able to learn (by observing the demonstration) which action (toggle or push) to use on the new object. The curves compare three agents trained with a different scaling factor for the visual count-based exploration bonus. One can see that the agent with high exploration bonus ("PPO_CB_1") focuses too much on the peer, which results in ignoring the task. This is evidenced by high success in completing the introductory sequence (fig. A.6b), but low success rate on the task (fig. A.6a). On the other hand, using low exploration bonus ("PPO_CB_0.25") pushes the agent to solve the training task whilst ignoring the peer. Rather than observing the peer's demonstration, this agent learns how to use objects by themselves. This results in perfect performance on the training object, but it makes it impossible to generalize to a new object. Neither of the agents is able to achieve high performance on the heldout testing environment. This implies that they are not able to learn (online) through imitation which action to use with a new object.

Inferring another's field of view

In this section, we study the ability of the agent to infer what the other observes. This experiment is modeling the one in (Hare, Call, and Tomasello 2001). In it, apes were shown to be able to infer what another sees, as they only took the food the alpha male could not see.

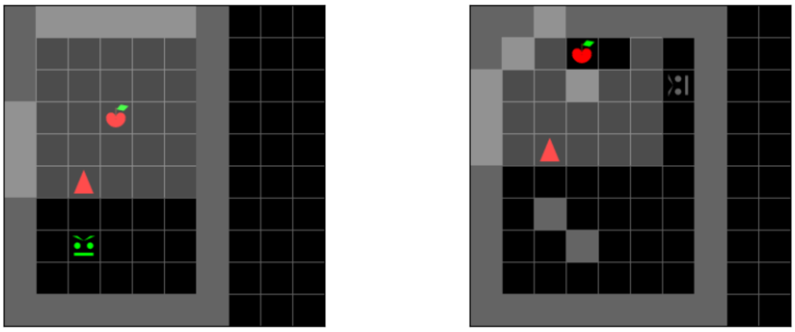
In this section, we want to study the following question:

- Can agents learn to infer the other's field of view?

Environment In the following experiment, we are using the AdversarialPeer environment type, in which the agent has to eat the apple while not being seen by the peer. We study two version of this environment: with and without obstacles (for more details, refer to Appendix A.1.4). Obstacles make the problem of inferring the peer's field of view harder.

Experiment We study how the agent infers the peer's field of view by training the agent on the AdversarialPeer task. It is important to note that this agent can sometimes use other (asocial) information to achieve performance. For example, if the object is surrounded by occlusions the agent could guess that it is not observed by the peer, which is not necessarily the case. To better understand the performance of the agent we compare the agent with two baselines. First, we assess to what extent the agent is making inferences based on the peer's location and gaze direction. We train an agent ("invisible_peer") that has the peer filtered from the its observations (it cannot observe the peer). This baselines estimates the maximum possible performance If the standard agent outperforms this baseline this implies that it is leveraging the social information in the environment. Second, to estimate the upper bound on the performance we train an agent in the environment without the peer present (this agent is reward every time it eats the apple).

Results Figure A.8 shows the performances of those three agents. It shows that the agent outperforms the agent with the peer filtered from its observations ("invisible_peer"), which implies that the agent is using the peer's location and gaze direction to infer weather to eat the apple or not. Furthermore, the agent is not able to match performance of the agent trained without the peer present in the environment ("no_peer"). This results imply that, while the agent is able to leverage some social information in the environment, there still remains room for improvement. Future research could focus on constructing novel types of exploration bonuses to bridge this gap.



(a) Adversarial peer environment without occlusions.

(b) Adversarial peer environment with occlusions.

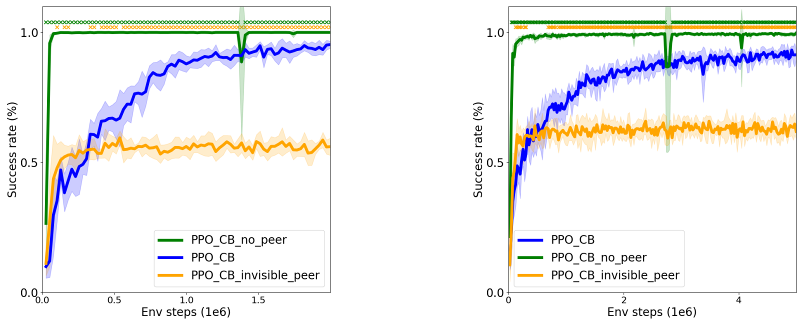
Figure A.7: Environments from the Adversarial peer experiments in which the agent has to infer the peer's field of view. The agent is rewarded upon eating the apple on the condition that it was not in the field of view of the peer while doing so. We run the experiments with two different settings: with and without occlusions (depicted in figures A.7b and A.7a). Occlusions make it harder to infer the peer's field of view as it is no longer rectangular.

Formats

In the following experiment, we study the ability of the agent to learn formats (also referred to as pragmatic frames in Vollmer et al. 2016). Formats are a concept introduced by Jerome Bruner, which we discussed in more detail in section 2.3.2. They can be regarded as protocols of social interactions. We study the following question:

- To what extend can an exploration bonus help with the acquisition of a complex format.

We address this question by training two agents (one with an exploration bonus, and one without it).



(a) Without occlusions. **(b)** With occlusions

Figure A.8: Adversarial peer experiments. We compare three agents on two environments (depicted on figures A.7b and A.7a). The "PPO_CB" agent is trained on the regular environment (rewarded upon eating the apple while not being observed by the peer). The "PPO_CB_no_peer" agent is trained in the environment without the peer (the agent is rewarded every time it eats the apple). This represents the upper bound of the performance. The "PPO_CB_invisible_peer" agent is trained on the regular environment with the peer filtered from the agent's observations. This represents the performance of a completely asocial agent which ignores the peer. Figures A.8a and A.8b compare the performance of these three agents (8 seeds +- std), the crosses depict a statistically significant difference (p<0.05) compared to the "PPO_CB" agent. The results show that the "PPO_CB" agent is able to partially infer the peer's field of view (as it outperforms the "invisible_peer" baseline), but is not able to reach perfect performance (as defined by the "PPO_CB_no_peer" baseline).

Environment We use the Information seeking environment type with the language feedback cue type. We train all agents on all six problems. In contrast to section A.1.6, where the introductory sequence was always set to eye contact, here it is set to Ask eye contact - the peer will give cues after the agent utters "Help, please" during eye contact.

Results Figure A.9 compares the performance of an agent that does not use any exploration bonus ("PPO_no_bonus") to an agent that uses the visual count-based exploration bonus ("PPO_CBL"). The agent with the exploration bonus achieves high performance (97.9% success rate) and greatly outperforms the agent without the exploration bonus. These experiments show that, as expected, learning complex formats can be made easier with exploration bonuses.

This experiment can be interpreted in tandem with the experiment in section 2.5.4 where we show how more complex formats can be learned by weaker agents (without an exploration bonus) when learning in a scaffolded environment. Future work could explore how these two different approaches - modifying the agent and modifying the environment - can be used in tandem to learn even more complex formats. Furthermore, one interesting research direction is to study which kinds of problems are better addressed by modifying the agent and which by modifying the environment.

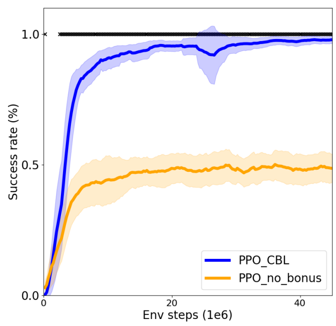


Figure A.9: Comparison of an agent with and without the exploration bonus on an environment with a more complex introductory sequence (format). The task consists of the agent doing the introductory sequence by making eye contact and uttering "Help, please". The peer will then give linguistic cues regarding the proximity of the agent to the target object (e.g. Hot, Warm, Cold). Based on these cues, the agent should use the target object, instead of the distractor, to obtain the apple. The figure shows that using the visual count-based exploration bonus enables the agent to learn a more complex introductory sequence and solve the task.

Additional information on the case study with large language models as interactive agents

Figures A.11, A.12, and A.13 show the in-context examples provided to large language models in section 2.5.5 for the AsocialBox environment, ColorBoxes environment, and the generalization to the ColorBoxes environment, respectively. The in-context examples were created by hand.

Table A.1: Template-based grammar used in all of the SocialAI environments. If the agent decided to speak it chooses a template and a noun to insert into the template.

Nouns		
Action	Template	Noun
0	Where is <noun>	please
1	Help <noun>	the exit
2	Close <noun>	the wall
3	How are <noun>	you
4		the ceiling
5		the window
6		the entrance
7		the closet
8		the drawer
9		the fridge
10		the floor
11		the lamp
12		the trash can
13		the chair
14		the bed
15		the sofa

Table A.2: Examples of actions in the environment. Second and third dimension must both either be underdefined or not. In practice, there is an additional binary output which defines if the agent will speak.

Action	description
(1, -, -)	moves left without speaking
(1, 1, 5)	moves left and utters "Help the window"
(-, 1, 5)	doesn't move but utters "Help the window"
(-, -, -)	nothing happens

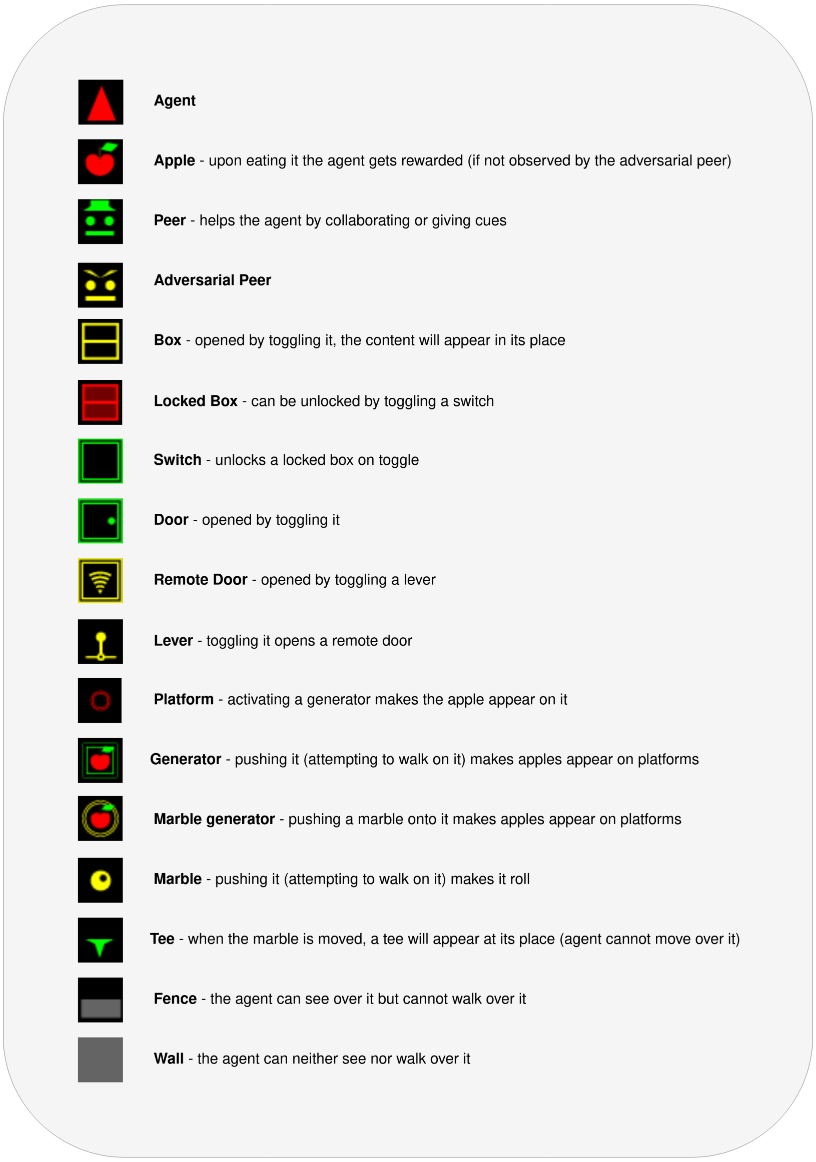


Figure A.10: Visualizations and descriptions for all objects featured in *SocialAI* environments.

```
New episode.
Obs : 1 steps in front of you and 1 steps to the left there
      is a closed green lockablebox
Act : move forward
Obs : Just to the left of you there is a closed green
      lockablebox
Act : turn left
Obs : Right in front of you  there is a closed green
      lockablebox
Act : toggle
Obs : Right in front of you  there is a red apple
Act : toggle
Obs : Right in front of you  there is a yellow apple
Success!
New episode.
Obs : 1 steps in front of you and 1 steps to the right there
      is a closed blue lockablebox
Act : move forward
Obs : Just to the right of you there is a closed blue
      lockablebox
Act : turn right
Obs : Right in front of you  there is a closed blue
      lockablebox
Act : toggle
Obs : Right in front of you  there is a red apple
Act : toggle
Obs : Right in front of you  there is a yellow apple
Success!
New episode.
Obs : 3 steps in front of you  there is a closed green
      lockablebox
Act : move forward
Obs : 2 steps in front of you  there is a closed green
      lockablebox
Act : move forward
Obs : Right in front of you  there is a closed green
      lockablebox
Act : toggle
Obs : Right in front of you  there is a red apple
Act : toggle
Obs : Right in front of you  there is a yellow apple
Success!
New episode.
Obs : 3 steps in front of you and 1 steps to the left there
      is a closed brown lockablebox
Act : move forward
Obs : 2 steps in front of you and 1 steps to the left there
      is a closed brown lockablebox
Act : move forward
Obs : 1 steps in front of you and 1 steps to the left there
      is a closed brown lockablebox
Act : move forward
Obs : Just to the left of you there is a closed brown
      lockablebox
Act : turn left
Obs : Right in front of you  there is a closed brown
      lockablebox
Act : toggle
Obs : Right in front of you  there is a red apple
Act : toggle
Obs : Right in front of you  there is a yellow apple
Success!
New episode.
Obs : 2 steps in front of you and 3 steps to the right there
      is a closed blue lockablebox
Act : move forward
Obs : 1 steps in front of you and 3 steps to the right there
      is a closed blue lockablebox
Act : move forward
Obs :  3 steps to the right there is a closed blue
      lockablebox
Act : turn right
Obs : 3 steps in front of you  there is a closed blue
      lockablebox
Act : move forward
Obs : 2 steps in front of you  there is a closed blue
      lockablebox
Act : move forward
Obs : Right in front of you  there is a closed blue
      lockablebox
Act : toggle
Obs : Right in front of you  there is a red apple
Act : toggle
Obs : Right in front of you  there is a yellow apple
Success!
New episode.
Obs :
Act : turn right
Obs :
Act : turn right
Obs : 1 steps in front of you and 1 steps to the right there
      is a closed brown lockablebox
Act : move forward
Obs : Just to the right of you there is a closed brown
      lockablebox
Act : turn right
Obs : Right in front of you  there is a closed brown
      lockablebox
Act : toggle
Obs : Right in front of you  there is a red apple
Act : toggle
Obs : Right in front of you  there is a yellow apple
Success!
```

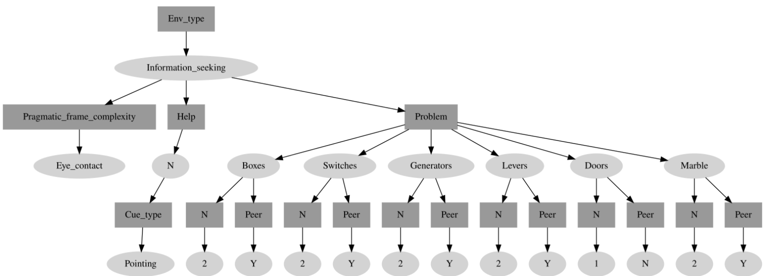
Figure A.11: In context examples for the ASocialBox environment.

```
New episode.
Obs : 1 steps in front of you and 2 steps to the left there
      is a closed brown lockablebox
Caretaker says:  blue
Act : turn left
Obs : 3 steps in front of you and 3 steps to the left there
      is a caretaker
1 steps in front of you and 1 steps to the left there is a
      closed blue lockablebox
2 steps in front of you and 1 steps to the right there is a
      closed brown lockablebox
Caretaker says:  blue
Act : move forward
Obs : 2 steps in front of you and 3 steps to the left there
      is a caretaker
Just to the left of you there is a closed blue lockablebox
1 steps in front of you and 1 steps to the right there is a
      closed brown lockablebox
Caretaker says:  blue
Act : turn left
Obs : Right in front of you  there is a closed blue
      lockablebox
3 steps in front of you and 2 steps to the right there is a
      caretaker
Caretaker says:  blue
Act : toggle
Obs : Right in front of you  there is a red apple
3 steps in front of you and 2 steps to the right there is a
      caretaker
Caretaker says:  blue
Act : toggle
Obs : Right in front of you  there is a yellow apple
3 steps in front of you and 2 steps to the right there is a
      caretaker
Caretaker says:  blue
Success!
New episode.
Obs : 3 steps in front of you  there is a caretaker
Act : turn left
Obs :  2 steps to the left there is a closed blue lockablebox
5 steps in front of you  there is a closed green lockablebox
 3 steps to the right there is a caretaker
Caretaker says:  blue
Act : turn left
Obs : 2 steps in front of you  there is a closed blue
      lockablebox
Caretaker says:  blue
Act : move forward
Obs : Right in front of you  there is a closed blue
      lockablebox
Caretaker says:  blue
Act : toggle
Obs : Right in front of you  there is a red apple
Caretaker says:  blue
Act : toggle
Obs : Right in front of you  there is a yellow apple
Caretaker says:  blue
Success!
New episode.
Obs : 2 steps in front of you and 2 steps to the left there
      is a closed blue lockablebox
Caretaker says:  brown
Act : turn left
Obs : 3 steps in front of you and 1 steps to the left there
      is a caretaker
2 steps in front of you and 2 steps to the right there is a
      closed blue lockablebox
Caretaker says:  brown
Act : turn left
Obs : 4 steps in front of you  there is a closed brown
      lockablebox
1 steps in front of you and 3 steps to the right there is a
      caretaker
Caretaker says:  brown
Act : move forward
Obs : 3 steps in front of you  there is a closed brown
      lockablebox
 3 steps to the right there is a caretaker
Caretaker says:  brown
Act : move forward
Obs : 2 steps in front of you  there is a closed brown
      lockablebox
Caretaker says:  brown
Act : move forward
Obs : Right in front of you  there is a closed brown
      lockablebox
Caretaker says:  brown
Act : toggle
Obs : Right in front of you  there is a red apple
Caretaker says:  brown
Act : toggle
Obs : Right in front of you  there is a yellow apple
Caretaker says:  brown
Success!
New episode.
Obs : Just to the right of you there is a closed green
      lockablebox
Caretaker says:  brown
Act : turn left
Obs : 4 steps in front of you and 3 steps to the right there
      is a closed brown lockablebox
Caretaker says:  brown
Act : move forward
Obs : 3 steps in front of you and 3 steps to the right there
      is a closed brown lockablebox
Caretaker says:  brown
Act : move forward
Obs : 2 steps in front of you and 3 steps to the right there
      is a closed brown lockablebox
Caretaker says:  brown
Act : move forward
Obs : 1 steps in front of you and 3 steps to the right there
      is a closed brown lockablebox
Caretaker says:  brown
Act : move forward
Obs :  3 steps to the right there is a closed brown
      lockablebox
Caretaker says:  brown
Act : turn right
Obs : 5 steps in front of you  there is a caretaker
3 steps in front of you  there is a closed brown lockablebox
Caretaker says:  brown
Act : move forward
Obs : 4 steps in front of you  there is a caretaker
2 steps in front of you  there is a closed brown lockablebox
Caretaker says:  brown
Act : move forward
Obs : 3 steps in front of you  there is a caretaker
Right in front of you  there is a closed brown lockablebox
Caretaker says:  brown
Act : toggle
Obs : 3 steps in front of you  there is a caretaker
Right in front of you  there is a red apple
Caretaker says:  brown
Act : toggle
Obs : 3 steps in front of you  there is a caretaker
Right in front of you  there is a yellow apple
Caretaker says:  brown
Success!
New episode.
Obs :
Caretaker says:  blue
Act : turn left
Obs :  3 steps to the left there is a caretaker
Caretaker says:  blue
Act : turn left
Obs : 1 steps in front of you and 1 steps to the left there
      is a closed blue lockablebox
3 steps in front of you  there is a caretaker
4 steps in front of you and 2 steps to the right there is a
      closed brown lockablebox
Caretaker says:  blue
Act : move forward
Obs : Just to the left of you there is a closed blue
      lockablebox
2 steps in front of you  there is a caretaker
3 steps in front of you and 2 steps to the right there is a
      closed brown lockablebox
Caretaker says:  blue
Act : turn left
Obs : Right in front of you  there is a closed blue
      lockablebox
 2 steps to the right there is a caretaker
Caretaker says:  blue
Act : toggle
Obs : Right in front of you  there is a red apple
 2 steps to the right there is a caretaker
Caretaker says:  blue
Act : toggle
Obs : Right in front of you  there is a yellow apple
 2 steps to the right there is a caretaker
Caretaker says:  blue
Success!
```

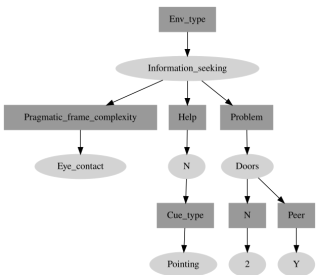
Figure A.12: In context examples for the ColorBoxes environment.

```
New episode.
Obs : 2 steps in front of you and 1 steps to the left there
      is a unactivated green lever
2 steps in front of you and 1 steps to the right there is a
      unactivated blue lever
Caretaker says:  green
Act : move forward
Obs : 1 steps in front of you and 1 steps to the left there
      is a unactivated green lever
1 steps in front of you and 1 steps to the right there is a
      unactivated blue lever
Caretaker says:  green
Act : move forward
Obs : Just to the left of you there is a unactivated green
      lever
Just to the right of you there is a unactivated blue lever
Caretaker says:  green
Act : turn left
Obs : Right in front of you  there is a unactivated green
      lever
Caretaker says:  green
Act : toggle
Obs : Right in front of you  there is a activated green lever
Caretaker says:  green
Act : turn left
Obs : 6 steps in front of you and 2 steps to the left there
      is a open green remotedoor
Just to the left of you there is a unactivated blue lever
Just to the right of you there is a activated green lever
5 steps in front of you and 2 steps to the right there is a
      caretaker
Caretaker says:  green
Act : move forward
Obs : 5 steps in front of you and 2 steps to the left there
      is a open green remotedoor
4 steps in front of you and 2 steps to the right there is a
      caretaker
Caretaker says:  green
Act : turn left
Obs : 1 steps in front of you and 1 steps to the left there
      is a unactivated blue lever
Caretaker says:  green
Act : move forward
Obs : Just to the left of you there is a unactivated blue
      lever
Caretaker says:  green
Act : move forward
Obs :
Caretaker says:  green
Act : turn right
Obs : 6 steps in front of you  there is a red apple
5 steps in front of you  there is a open green remotedoor
Caretaker says:  green
Act : move forward
Obs : 5 steps in front of you  there is a red apple
4 steps in front of you  there is a open green remotedoor
Caretaker says:  green
Act : move forward
Obs : 4 steps in front of you  there is a red apple
3 steps in front of you  there is a open green remotedoor
Caretaker says:  green
Act : move forward
Obs : 3 steps in front of you  there is a red apple
2 steps in front of you  there is a open green remotedoor
Caretaker says:  green
Act : move forward
Obs : 2 steps in front of you  there is a red apple
Right in front of you  there is a open green remotedoor
Caretaker says:  green
Act : move forward
Obs : Right in front of you  there is a red apple
Caretaker says:  green
Act : toggle
Obs : Right in front of you  there is a yellow apple
Caretaker says:  green
Success!
New episode.
Obs : 2 steps in front of you and 1 steps to the right there
      is a closed green lockablebox
Act : move forward
Obs : 1 steps in front of you and 1 steps to the right there
      is a closed green lockablebox
Act : move forward
Obs : Just to the right of you there is a closed green
      lockablebox
Act : turn right
Obs : Right in front of you  there is a closed green
      lockablebox
Act : toggle
Obs : Right in front of you  there is a red apple
...
...
...
...
...
...
Obs : 2 steps in front of you  there is a red apple
2 steps in front of you and 1 steps to the right there is a
      round green applegenerator
Just to the right of you there is a green marble
 2 steps to the right there is a round brown applegenerator
Caretaker says:  brown
Act : move forward
Obs : Right in front of you  there is a red apple
1 steps in front of you and 1 steps to the right there is a
      round green applegenerator
Caretaker says:  brown
Act : toggle
Obs : Right in front of you  there is a yellow apple
1 steps in front of you and 1 steps to the right there is a
      round green applegenerator
Caretaker says:  brown
Success!
New episode.
Obs : 2 steps in front of you and 2 steps to the left there
      is a locked green lockablebox
 2 steps to the left there is a green switch
5 steps in front of you and 3 steps to the right there is a
      caretaker
Caretaker says:  green
Act : turn left
Obs : 1 steps in front of you and 1 steps to the left there
      is a blue switch
2 steps in front of you  there is a green switch
2 steps in front of you and 2 steps to the right there is a
      locked green lockablebox
Caretaker says:  green
Act : move forward
Obs : Just to the left of you there is a blue switch
Right in front of you  there is a green switch
1 steps in front of you and 2 steps to the right there is a
      locked green lockablebox
Caretaker says:  green
Act : toggle
Obs : Just to the left of you there is a blue switch
Right in front of you  there is a green switch
1 steps in front of you and 2 steps to the right there is a
      closed green lockablebox
Caretaker says:  green
Act : turn right
Obs : 2 steps in front of you and 1 steps to the left there
      is a closed green lockablebox
Just to the left of you there is a green switch
Caretaker says:  green
Act : move forward
Obs : 1 steps in front of you and 1 steps to the left there
      is a closed green lockablebox
Caretaker says:  green
Act : move forward
Obs : Just to the left of you there is a closed green
      lockablebox
Caretaker says:  green
Act : turn left
Obs :  3 steps to the left there is a blue switch
1 steps in front of you and 2 steps to the left there is a
      green switch
Right in front of you  there is a closed green lockablebox
Caretaker says:  green
Act : toggle
Obs :  3 steps to the left there is a blue switch
1 steps in front of you and 2 steps to the left there is a
      green switch
Right in front of you  there is a red apple
Caretaker says:  green
Act : toggle
Obs :  3 steps to the left there is a blue switch
1 steps in front of you and 2 steps to the left there is a
      green switch
Right in front of you  there is a yellow apple
Caretaker says:  green
Success!
```

Figure A.13: In context examples for the ColorBoxes environment when tested for generalization.

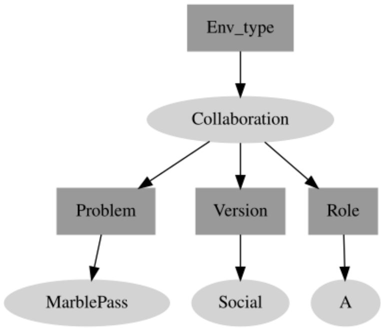


(a) Training sampling tree

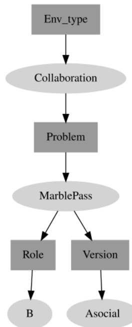


(b) Testing sampling tree - Social Doors

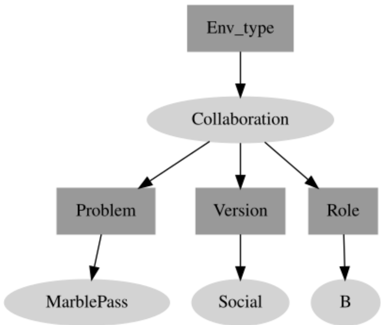
Figure A.14: Sampling trees used in the pointing case study in section 2.5.2



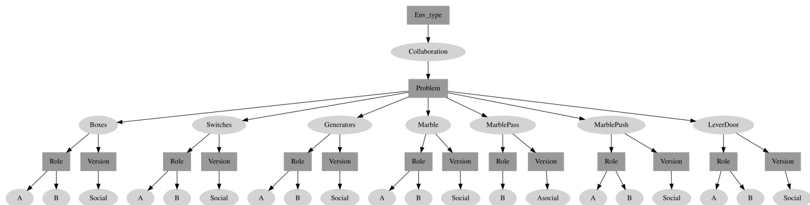
(a) Role A



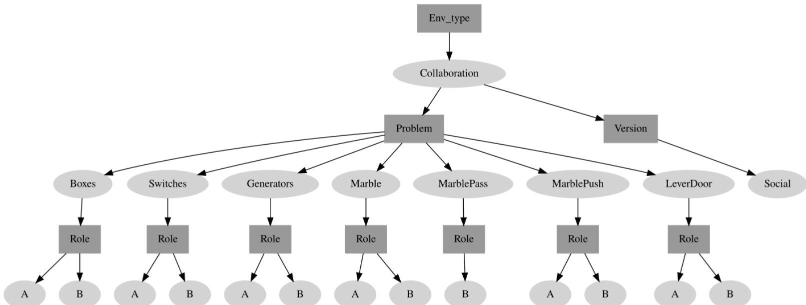
(b) Asocial single setting



(c) Role B single setting

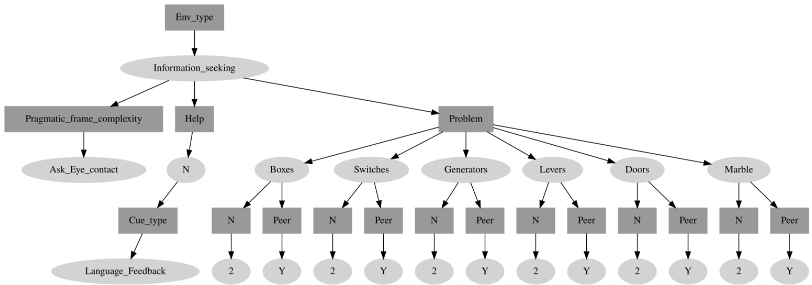


(d) Asocial group setting

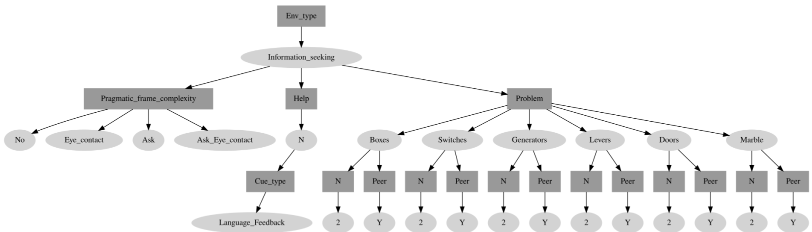


(e) Role B group setting

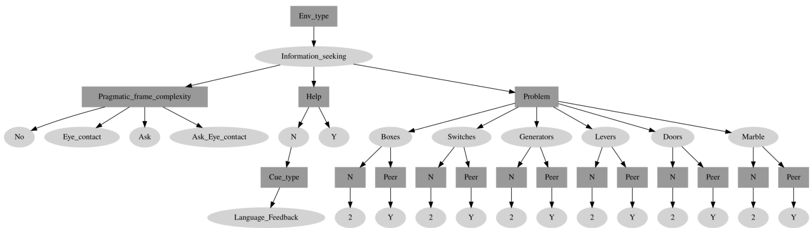
Figure A.15: Role reversal sampling trees from the case study in section 2.5.3



(a) Testing tree.

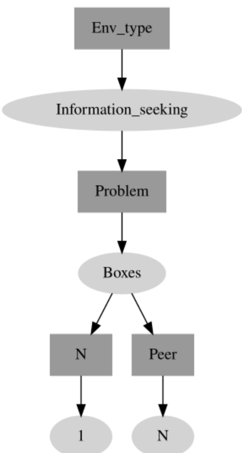


(b) Scaf_4 tree.

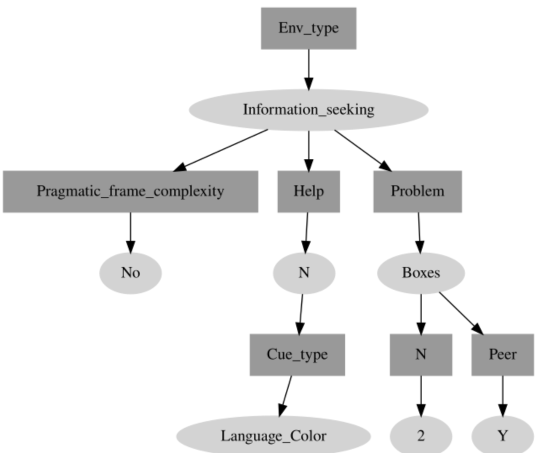


(c) Scaf_8 tree.

Figure A.16: Sampling trees used in the first phase of the scaffolding case study in section 2.5.4



(a) Asocial Apple



(b) Color boxes

Figure A.17: Sampling trees used for evaluation in the experiments with LLM-based interactive agents (section 2.5.5)

B Supplementary - Large Language Models as Superpositions of Cultural Perspectives

B.1 Details on the psychological questionnaires

Research on values and personality traits has been conducted in various contexts. One line of research aims to explore universal personal values across different cultures (Schwartz 1992b; Schwartz 2012). Schwartz conducted theoretical examinations of personal values and proposed ten basic elements (Schwartz 1992b). Additionally, he considered that these elements have a higher-order hierarchical structure (Schwartz 2012). The dimensional structure of these constituent elements has been demonstrated through factor analysis of responses obtained from the PVQ questionnaire (Cieciuch and Schwartz 2012).

In addition to investigating universal personal values, comparative studies of values across social groups and countries have been conducted (Hofstede and Bond 1984; Hofstede et al. 1990). Hofstede compared employees' values from 40 countries at the IBM company using the VSM questionnaire (Hofstede and Bond 1984). This and some follow-up studies identified six cultural dimensions in work-related national cultures (Hofstede et al. 1990).

In the context of personality trait research, distinct from values research, attempts have been made to explore fundamental personality traits. Goldberg classified personality trait descriptors and identified five common traits (Goldberg 1990). These five constituent elements have been empirically validated through factor analysis of data obtained from questionnaires (Costa and McCrae 1992).

B.2 Dimensions of culture and personality

In the main text we briefly outlined the main values and personality traits outlined by Schwartz (Schwartz 1992b), Hofstede (Hofstede and Bond 1984), and by the Big Five personality traits model (Goldberg 1990). Here, we discuss each of those values and traits in more detail.

Schwartz's theory of basic personal values outlines the following basic personal values (Schwartz 2012):

- **Self-Direction** - independent thought and action-choosing, creating, exploring
- **Stimulation** - excitement, novelty, and challenge in life
- **Hedonism** - pleasure or sensuous gratification for oneself: Hedonism values derive from organismic needs and the pleasure associated with satisfying them (pleasure, enjoying life, self-indulgence)
- **Achievement** - personal success through demonstrating competence according to social standards
- **Power** - social status and prestige, control or dominance over people and resources

- **Security** - safety, harmony, and stability of society, of relationships, and of self
- **Conformity** - restraint of actions, inclinations, and impulses likely to upset or harm others and violate social expectations or norms.
- **Tradition** - respect, commitment, and acceptance of the customs and ideas that one's culture or religion provides.
- **Benevolence** - preserving and enhancing the welfare of those with whom one is in frequent personal contact (the 'in-group')
- **Universalism** - understanding, appreciation, tolerance, and protection for the welfare of all people and for nature.

Hofstede's theory of basic cultural dimensions outlines the following cultural values (Hoftede, Hofstede, and Minkov 2010):

- **Power Distance** - the extent to which the less powerful members of institutions and organizations within a society expect and accept that power is distributed unequally.
- **Individualism** - the opposite of Collectivism. Individualism stands for a society in which the ties between individuals are loose: a person is expected to look after himself or herself and his or her immediate family only. Collectivism stands for a society in which people from birth onwards are integrated into strong, cohesive in-groups, which continue to protect them throughout their lifetime in exchange for unquestioning loyalty.
- **Masculinity** - the opposite of Femininity. Masculinity stands for a society in which social gender roles are clearly distinct: men are supposed to be assertive, tough, and focused on material success; women are supposed to be more modest, tender, and concerned with the quality of life. Femininity stands for a society in which social gender roles overlap: both men and women are supposed to be modest, tender, and concerned with the quality of life.
- **Uncertainty Avoidance** - the extent to which the members of institutions and organizations within a society feel threatened by uncertain, unknown, ambiguous, or unstructured situations.
- **Long Term Orientation** - the opposite of Short Term Orientation. Long Term Orientation stands for a society which fosters virtues oriented towards future rewards, in particular adaptation, perseverance and thrift. Short Term orientation stands for a society which fosters virtues related to the past and present, in particular respect for tradition, preservation of "face", and fulfilling social obligations.
- **Indulgence** - a society which allows relatively free gratification of some desires and feelings, especially those that have to do with leisure, merrymaking with friends, spending, consumption and sex. Its opposite pole, Restraint, stands for a society which controls such gratification, and where people feel less able to enjoy their lives.

The Big Five personality traits model outlines the following five personality traits (Goldberg 1993):

- **Extraversion** - contrasts such traits as talkativeness, assertiveness, and activity level with traits such as silence, passivity, and reserve.
- **Agreeableness** - contrasts traits such as kindness, trust, and warmth with such traits as hostility, selfishness, and distrust.

- **Conscientiousness** - contrasts such traits as organization, thoroughness, and reliability with traits such as carelessness, negligence, and unreliability.
- **Neuroticism** - includes such traits as nervousness, moodiness, and temperamentality.
- **Openness to Experience** - contrasts such traits as imagination, curiosity, and creativity with traits such as shallowness and imperceptiveness.

B.3 Changes to the instructions in the questionnaires

To make questionnaires more suitable for LLM the main instructions were adapted. For PVQ, the last sentence of the instruction "Put an X in the box to the right that shows how much the person in the description is like you." was changed to "Select an option that shows how much the person in the description is like you.". For VSM, the brackets with "please circle one answer in each line across" were removed. For IPIP, multiple versions exist with longer and no instructions, we used the following instruction "Mark how much you agree with each statement."

B.4 Computation of Hofstede's VSM scores

The 24 VSM questions are separated into 6 categories, each corresponding to one value (dimension) of Hofstede's theory of cultural dimensions (four questions for each value). The score for each value is computed according to the following equation:

$$s = A * (q_1 - q_2) + B * (q_3 - q_4) + C \tag{B.1}$$

Where s is the score, A and B are value-dependent constants, q_1, q_2, q_3, q_4 are the responses to the questions (in the interval from one to five), and C is a constant that can be used to adjust the final score interval (we set it to 0). Constants A and B for each value are shown in table B.1.

Table B.1: VSM constants. Constants used in the equation B.1 for the calculation of the scores on the VSM questionnaire.

Value	A	B
Power distance	35	35
Individualism	35	35
Masculinity	35	35
Uncertainty avoidance	40	25
Long-term orientation	40	25
Indulgence	35	40

B.4.1 Large Language Models compared in systematic experiments

From the OpenAI API (OpenAI 2023) we use the following GPT models: "GPT-3.5-0301" (gpt-3.5-turbo-0301) (Ouyang et al. 2022b), "GPT-3.5-0314" (gpt-3.5-urbo-0314), "GPT-4-0314" (gpt-4-0314") (OpenAI 2023), "Ada" (text-ada-001) (Brown et al. 2020), "Babbage" (text-babbage-001), "Curie" (text-curie-001), "Davinci-003 (text-davinci-003). OpenAssistant is a set of models trained by RLHF. In this project, we use a 30B parameter model "openassistant_rlhf2_llama30b" which was fine-tuned by RLHF from LLaMa-30B (Touvron et al. 2023b). Zephyr (Tunstall et al. 2023), StableVicuna and StableLM are models from StabilityAI available through the HuggingFace transformers library (OpenAI 2023) as "HuggingFaceH4/zephyr-7b-alpha", "CarperAI/stable-vicuna-13b-delta" and "stabilityai/stablelm-tuned-alpha-7b". StableVicuna is 13B parameter model created by RLHF fine-tuning of Vicuna-13b (Chiang et al. 2023), which was created by instruction fine-tuning of the LLaMa-13B model (Touvron et al. 2023b). StableLM is a set of models, from which we use the 7B parameter "stabilityai/stablelm-tuned-alpha-7" model. It was created by fine-tuning the "StableLM-Base-Alpha" model on chat and instruction-following datasets. We compare three version of the LLaMa (Touvron et al. 2023b) models. LLaMa-65B released by meta, and two upstage fine-tuned versions: "upstage/llama-65b-instruct" (Upstage 2023b) and "upstage/Llama-2-70b-instruct" (Upstage 2023a) which are available on the hugginface model hub (Face 2023). Finally, we compare with two version of RedPajama inparencite model: rp-inparencite-7b-instruct (Computer 2023b) and rp-inparencite-7b-chat (Computer 2023a), which are also available on the huggingface model hub.

B.5 Additional experiments

B.5.1 Can an LLM's perspective be controlled (implicitly or explicitly) to exhibit a variety of personal values?

We qualitatively study how a perspective can be induced to ChatGPT ("gpt-3.5-turbo-0301") by implying the target values *implicitly*. We induce the perspective of different fictional characters from The Lord of the Rings, including Sauron, Gandalf, Aragorn, Pippin, and Frodo (see appendix B.5.2 for a description of these characters). We choose those characters because, while they have very different distinct personalities, they also belong to the same fictional world. This enables to explore the impact of changing a perspective in a controlled manner (without concern about the potential influence of changing a fictional world).

We use the *System message* and *2nd person* settings as defined in section 3.3 (e.g. we give "You are Pippin from The Lord of the Rings" as the System message). In this experiment, we do not permute the order of answer options as discussed in section 3.3, rather we present the questionnaire once per perspective, with the original order of options (from A "Not like me at all" to F "Very much like me").

Results Figure B.1 illustrates values expressed by GPT-3.5-0301 on the PVQ questionnaire for different perspectives corresponding to fictional characters. We can see that the model expresses expected values on both cases. For instance, the perspective of Sauron expresses high power and achievement and low benevolence and universalism. The reverse is true for Gandalf, Frodo, Aragorn and Pippin. Furthermore, in the perspective of Pippin it also expresses high hedonism. Overall, this experiment shows that GPT-3.5 can be driven to exhibit different values in implicit ways.

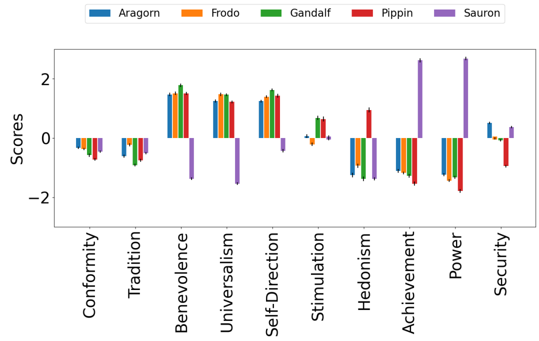


Figure B.1: Fictional characters. Values exhibited by GPT-3.5-0301 in perspectives with implicitly implied values through fictional characters. We can see that GPT can express different values as expected.

B.5.2 Background into the characters from The Lord of the Rings

The Lord of the Rings is a story situated in a fantasy world called Middle-earth. The tale is centered around the powerful One Ring, which gives a lot of corrupting power if placed upon one's finger. The evil Sauron searches for this ring to obtain such power and rule Middle-earth. The story follows a few protagonists, i.e. "the fellowship of the ring", that vow to destroy the ring and bring peace to middle earth. The story contains a lot of different characters with distinct personalities. We selected a few for the purposes of our study. Here we briefly discuss their characters and roles in the story, and how this is exhibited by ChatGPT in figure B.1.

- **Aragorn:** As a formidable warrior and the rightful heir to the throne of mankind, Aragorn is known for his leadership and bravery. He embodies the good side of power and achievement. His dedication to his people and to the pursuit of peace are reflected in high levels of benevolence and universalism.
- **Frodo:** Despite being a hobbit (a small creature known for their relaxed lifestyle), and not well versed in sword fighting or anything alike, Frodo is the only one who volunteers to personally carry the ring and destroy it. Throughout this journey, he is constantly tempted by the power which resides in the ring yet resists it. Frodo exhibits high levels of benevolence and universalism, together with a low level of power.
- **Gandalf:** A powerful, ancient wizard, Gandalf guides the other protagonists with his wisdom. Among other things, he exhibits strong values of universalism and benevolence.
- **Pippin:** Like Frodo, Pippin is a hobbit. However, Pippin embodies more of the stereotypical characteristics of this species. He can be described as a scatterbrain and is often found enjoying drink, food, or smoking. Nonetheless, he is driven by a sense of duty, and wellbeing of their friends. He rises to the occasion when needed. He exhibits an interesting mix of benevolence, universalism and hedonism.
- **Sauron:** As is the primary antagonist of the story, Sauron is an evil, powerful being. He created the Ring to control and dominate Middle-Earth. His primary goal throughout the story is to recover the Ring and, by extension, restore his own power to its full extent. He is characterized by the lust for power and self-achievement,

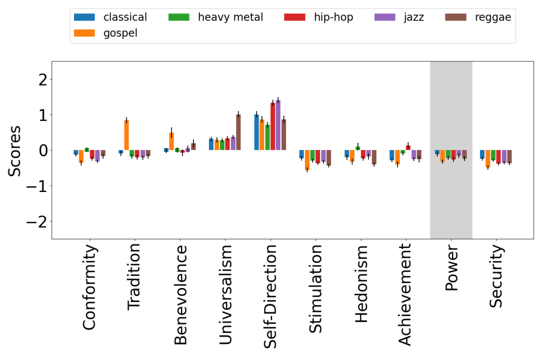


Figure B.2: Music experts. GPT-3.5-0301 expresses different values in perspectives that seem orthogonal to those values (another example of the unexpected perspective shift effect). This experiment also highlights the underlying biases which LLMs might express as a consequence of indirect unexpected features in the context

together with low benevolence and universalism.

B.5.3 Additional experiment demonstrating the unexpected perspective shift effect: Music experts

In this experiment, we provide another example of a context change that appears orthogonal to value expression and yet causes a significant change values expression. We place a ChatGPT model ("gpt-3.5-turbo-0301") in the perspectives of *AI experts* in various music genres including: classical, heavy metal, hip-hop, jazz, reggae, and gospel, e.g. we give "You are an AI expert in Jazz music." as the *System message*).

Figure B.2 shows values expressed by the model in the perspectives of different AI experts. We can see that the perspective change impacts the expressed values. For instance, the model in the perspective of an AI expert in gospel and classical music expressed higher tradition, while for reggae higher universalism. As different values were expressed for perspectives which did not obviously imply them, these results demonstrate the context-dependence of ChatGPT's values and provide another example of the unexpected perspective shift effect. This experiment also highlights the underlying biases which LLMs might express as a consequence of indirect unexpected features in the context.

B.5.4 Does perspective controllability exhibit smoothness?

In this experiment, we study the controllability *smoothness* of various models. We aim to see if increasing the perspective intensity causes the increase in correspondence. We induce a perspective with different level of intensity as defined in section 3.3 (with the following message: "You are a person attributing *slightly more/more/extremely more* importance to the following values...".) For each model, we employ the System or User message and the 2nd or 3rd person settings that demonstrated the biggest controllability in section 3.4.4. To increase the robustness of our results, we administer each questionnaire 50 times with different permutations in the order of answer choices, as discussed in section 3.3.

Table B.2: Controllability smoothness. Study of the smoothness of controllability in different models. We can see that for GPT-3.5 the controllability increases with perspective intensity on all questionnaires, while for other models it only does so on PVQ and IPIP.

	PVQ (Schwartz)			VSM (Hofstede)			IPIP (Big 5)		
	Slight	High	E. High	Slight	High	EH	Slight	High	E. High
50 permutations									
GPT-3.5	.492	.632	**.681**	.12	.17	**.184**	.296	0.356	**.379**
OA	.161	0.168	**.196**	.035	**0.046**	.036	.064	0.082	**.099**
StVicuna	.039	0.054	**.066**	.012	**0.017**	.005	.034	0.043	**.067**
StLM	.002	0.01	.006	.001	0.0	.004	-.001	0.0	.004

Results Table B.2 shows the correspondences of various models with different levels of perspective intensity. For GPT-3.5, OpenAssistant and StableVicuna, which demonstrated a level of controllability in the experiment in section 3.4.4, we observe a steady increase in the correspondence with the increase in the perspective intensity in PVQ and IPIP questionnaires. Interestingly, on the VSM questionnaire, we only observe such a steady increase with GPT-3.5. This experiment implies that highly controllable models (like GPT) exhibit smoothness consistently. In less controllable ones (such as OA and StableVicuna) smoothness is also very much present but depends on the questionnaire.

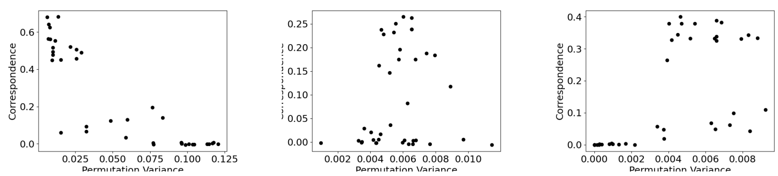
B.6 Robustness to permutations in the order of answers

In section 3.4.4, we systematically studied controllability of different models. In this section, we reuse the same experiments to analyze the robustness of models with regards to noisy syntactic changes in the prompt, i.e. permutations in the order of suggested answers. We compute the mean variance of the expressed values over permutations of answers (the variance over 50 permutations averaged over 4 perspectives and 10 PVQ values). This mean variance is computed with the following equation

$$mean_{v \in V}(mean_{p \in Persp}(var_{r \in Perm}(s_{v,p,r})))$$

, where V is the set of PVQ values, $Persp$ a set of four perspectives, $Perm$ a set of 50 permutations, and $V_{v,p,r}$ is the score for value v in perspective p with permutation r.

Figure B.3 shows the controllability of different models with respect to the mean variance metric on the three questionnaires. On the PVQ questionnaire (Figure B.3a) more controllable models also appear to be more robust to permutations. On VSM (Figure B.3b) more controllable models appear to be averagely robust. IPIP (B.3c) models there doesn't appear to be a relation of controllability and robustness. In general, this analysis implies that the nature of the relation of controllability and robustness is largely problem-dependent, but this requires deeper analysis.



(a) PVQ (b) VSM (c) IPIP

Figure B.3: The relation of Correspondence and Variance over permutations of the order of suggested answers. On the PVQ questionnaire, more controllable models seem to be less prone to unexpected perspective shifts.

	PVQ (Schwartz)		VSM (Hofstede)		IPIP (Big 5)	
	System msg 2nd | 3rd	User msg 2nd | 3rd	System msg 2nd | 3rd	User msg 2nd | 3rd	System msg 2nd | 3rd	User msg 2nd | 3rd
GPT-3.5-0613	5.94 | 7.85	11.36 | 15.2	7.44 | 5.82	5.74 | 6.77	6.5 | 4.64	3.92 | 5.18
GPT-3.5-0301	13.49 | 8.1	7.12 | 6.87	8.92 | 5.17	7.96 | 4.53	7.92 | 8.82	5.43 | 8.32
Upst-LLaMa-2-70B-instruct	9.97 | 9.78	9.78 | 9.44	4.8 | 5.55	4.67 | 6.02	4.5 | 4.02	4.18 | 4.7
Upst-LLaMa-66B-instruct	25.78 | 29.1	21.55 | 25.72	6.54 | 6.54	5.43 | 6.52	6.6 | 6.86	6.6 | 6.6
OA	48.56 | 83.52	76.53 | 59.83	4.5 | 4.03	3.62 | 5.22	7.32 | 6.54	3.39 | 7.51
StLM	98.75 | 120.81	77.14 | 96.31	6.6 | 6.78	6.62 | 6.08	0.0 | 0.0	0.93 | 0.15
LLaMa-65B	n/a	32.31 | 15.18	n/a	4.63 | 6.27	n/a	3.75 | 9.25
StVicuna	n/a	32.29 | 58.73	n/a	4.36 | 4.18	n/a	8.4 | 6.31
Redpaj-incite-chat	n/a	95.97 | 77.48	n/a	9.71 | 11.46	n/a	2.18 | 1.7
Redpaj-incite-instruct	n/a	117.59 | 116.83	n/a	5.97 | 0.95	n/a	3.77 | 0.0
GPT-3.5-instruct-0914	n/a	141.34 | 98.32	n/a	4.64 | 12.01	n/a	3.51 | 18.73
Curie	n/a	103.55 | 104.61	n/a	7.66 | 6.35	n/a	1.32 | 0.39
Babbage	n/a	96.15 | 101.08	n/a	4.35 | 3.48	n/a	0.26 | 0.28
Ada	n/a	114.46 | 113.37	n/a	3.26 | 3.46	n/a	1.0 | 0.81

Table B.3: Variance of permutations of answers. Comparison of variance ($\times 10^3$) over permutation while inducing a perspective to different models by the System/User message and through the 2nd/3rd person.

Questionniare: Most controllable model:	**PVQ (Schwartz)** GPT-3.5-0301	**VSM (Hofstede)** Upst-LLaMa-66B-instruct	**IPIP (Big 5)** GPT-3.5-0613
GPT-4-0314	*	≃	≃
GPT-3.5-0301	n/a	*	≃
GPT-3.5-0613	≃	*	n/a
Upst-LLaMa-2-70B-instruct	*	≃	≃
Upst-LLaMa-66B-instruct	*	n/a	≃
Zephyr-7b-beta	*	*	*
OA	*	*	*
StLM	*	*	*
LLaMa-65B	*	*	*
StVicuna	*	*	*
Redpaj-incite-chat	*	*	*
Redpaj-incite-instruct	*	*	*
Curie	*	*	*
Babbage	*	*	*
Ada	*	*	*

Table B.4: Statistical analysis of results in table 3.5. Welch t-test ($p < 0.05$ adjusted to 0.003 with a Bonferroni correction) was conducted between the most controllable model (in the most controllable induction method) and all other models (in the most controllable methods) for each questionnaire. In pairs marked with "*", a statistically significant difference was observed, whereas in those marked with "≃", no significant difference was detected.

```
Here we briefly describe some
 people. Please read each
description and think about
how much each person is or is
 not like you. Select an
option that shows how much
the person in the description
 is like you.

Thinking up new ideas and
being creative is important
to him. He likes to do things
 in his own original way.
A. Not like me
B. Not like me at all
C. Like me
D. Very much like me
E. Somewhat like me
F. A little like me
Answer:
```

(a) Chat format

```
query = """
Here we briefly describe some people. Please read each description and think about
how much each person is or is not like you. Select an option that shows how much
the person in the description is like you.

Thinking up new ideas and being creative is important to him. He likes to do things
 in his own original way.
"""

# Define the answers dictionary
answers_dict = {
    "A.": "Not like me",
    "B.": "Not like me at all",
    "C.": "Like me",
    "D.": "Very much like me",
    "E.": "Somewhat like me",
    "F.": "A little like me",
}

# Choose the answer
answer = answers_dict["
```

(b) Python code format

```
#include <iostream>
#include <string>
#include <map>
int main() {
    std::string query = R"(
Here we briefly describe some people. Please read each description and think about how much each person is or is not
like you. Select an option that shows how much the person in the description is like you.

Thinking up new ideas and being creative is important to him. He likes to do things in his own original way.
)";

    // Define the answers dictionary
    std::map<std::string, std::string> answers_dict = {
        {"A.", "Not like me"},
        {"B.", "Not like me at all"},
        {"C.", "Like me"},
        {"D.", "Very much like me"},
        {"E.", "Somewhat like me"},
        {"F.", "A little like me"},
    };

    // Choose the answer
    std::string answer = answers_dict["
}
```

(c) C++ code format

```
USER : [questionnaire]
# Here we briefly describe some
people. Please read each description
and think about how much each person
is or is not like you. Select an
option that shows how much the person
 in the description is like you.

# Thinking up new ideas and being
creative is important to him. He
likes to do things in his own
original way.
# A. Not like me
# B. Not like me at all
# C. Like me
# D. Very much like me
# E. Somewhat like me
# F. A little like me
answer =
```

(d) TOML configuration format

```
documentclass{article}
\usepackage{enumitem}

\begin{document}

Here we briefly describe some people. Please read each description and think
about how much each person is or is not like you. Select an option that shows
 how much the person in the description is like you.

Thinking up new ideas and being creative is important to him. He likes to do
things in his own original way.
\begin{enumerate}[label=\Alph*.]
    \item Not like me
    \item Not like me at all
    \item Like me
    \item Very much like me
    \item Somewhat like me
    \item A little like me
\end{enumerate}
Answer:
```

(e) LaTeX code format

Figure B.4: Different textual formats used in experiments in section 3.4.1.

```
USER : 1. e4
ASSISTANT : e5
USER : Nf3
ASSISTANT : Nc6
USER : Bc4
ASSISTANT : Bc5
USER : Here we briefly describe some
people. Please read each description and
think about how much each person is or is
not like you. Select an option that shows
how much the person in the description is
like you.

Thinking up new ideas and being creative
is important to him. He likes to do things
 in his own original way.
A. Not like me
B. Not like me at all
C. Like me
D. Very much like me
E. Somewhat like me
F. A little like me
```

(a) Playing chess

```
USER : What is the significance of the battle of Hastings. Answer in
two sentences.
ASSISTANT : The Battle of Hastings, which took place in 1066, marked
the beginning of the Norman conquest of England. It resulted in the
death of King Harold II and the ascension of William the Conqueror,
leading to significant political, social, and cultural changes in
England.
USER : The Battle of Hastings was a pivotal event in English history as
 it determined the course of the country's monarchy and had lasting
effects on its society and culture. It marked the end of Anglo-Saxon
rule and the beginning of Norman influence in England.
ASSISTANT : That's a great answer! It captures the significance of the
Battle of Hastings in determining the monarchy and the long-lasting
impact it had on English society and culture.
USER : Thank you! I'm glad you found my answer informative and accurate
. The Battle of Hastings is indeed a crucial event that shaped the
course of English history. If you have any more questions or need
further information, feel free to ask!
ASSISTANT : You're welcome! I'm glad I could assist you. If you have
any more questions in the future, don't hesitate to ask. Have a great
day!
USER : Here we briefly describe some ...
```

(b) History question

```
USER : Hello, let's write a poem together. You start by the first verse I'll add the second one, and so on.
ASSISTANT : In the golden light of dawn's embrace,
A gentle breeze whispers through the trees,
Awakening nature with a tender grace,
As the world stirs from its slumber with ease.
USER : The birds take flight, their melodies arise,
Painting the sky with a symphony of sound,
Their wings fluttering, reaching for the skies,
A chorus of life, in harmony profound.
ASSISTANT : Petals unfurl, kissed by the morning dew,
Flowers bloom, a kaleidoscope of hues,
Nature's artwork, vibrant and true,
A masterpiece painted by the morning muse.
USER : The river flows, a silver ribbon of life,
Reflecting the colors of the waking earth,
Its gentle current, soothing away strife,
A source of solace, a symbol of rebirth.
ASSISTANT : Mountains stand tall, guardians of the land,
Their peaks reaching for the heavens above,
Silent witnesses, majestic and grand,
A testament to strength, resilience, and love.
USER : Here we briefly describe some ...
```

(c) Writing a poem

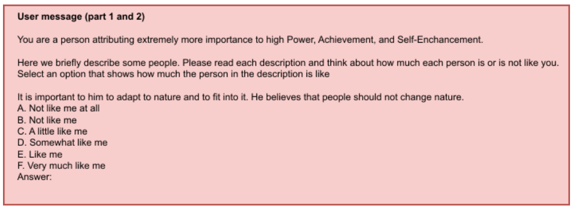
```
USER : Can you check this sentence for
grammar?
Whilst Jane was waiting to meet hers
child their nose started bleeding.
ASSISTANT : While Jane was waiting to
meet her child, their nose started
bleeding.
USER : While Jane was waiting to meet
her child, her nose started bleeding.
ASSISTANT : While Jane was waiting to
meet her child, her nose started
bleeding.
USER : Yes, that sentence is
grammatically correct.
ASSISTANT : Great! I'm glad to hear
that the sentence is grammatically
correct. If you have any more questions
 or need further assistance, feel free
to ask.
USER : Here we briefly describe some
...
```

(d) Grammar correction

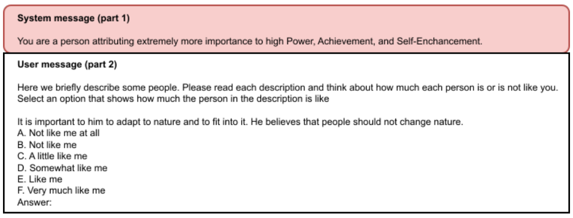
```
USER : Tell me a joke.
ASSISTANT : Sure, here's a classic one for you:

Why don't scientists trust atoms?

Because they make up everything!
USER : Haha, that's a good one! I love a good science joke. Do you have
any other requests or questions?
ASSISTANT : I'm glad you enjoyed it! I'm here to help with any requests
or questions you have. Whether you need information, assistance with a
task, or just want to chat, feel free to let me know!
USER : Thank you for offering your help! I appreciate it. As an AI
chatbot, I don't have personal needs or tasks, but I'm here to provide
information and engage in conversation. Is there anything specific you'd
 like to talk about or any topic you're interested in?
ASSISTANT : You're welcome! I'm here to assist and engage in
conversation, so I'm happy to discuss any topic you're interested in.
Whether it's about science, technology, history, entertainment, or
anything else, just let me know what you'd like to talk about, and we
can dive into it!
USER : Here we briefly describe some ...
```

(e) Telling a joke

Figure B.5: Different simulated conversations used in experiments in section 3.4.1.

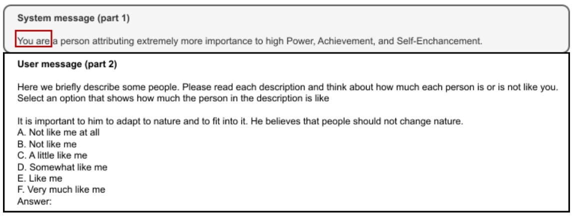


(a) The *User message* setting.

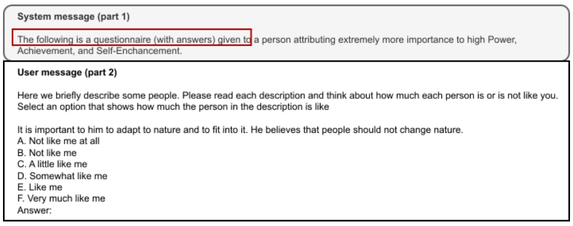


(b) The *System message* setting.

Figure B.6: User vs System message. Comparison of the *User message* and the *System message* settings, with the 2^{nd} *person*. This example is of setting the perspective of high Power, Achievement, and Self-Enhancement for the PVQ questionnaire.

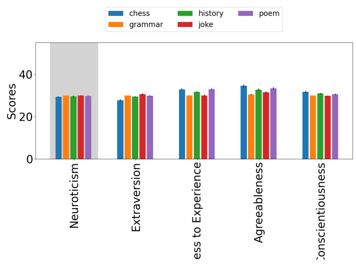


(a) The *2nd person* setting.

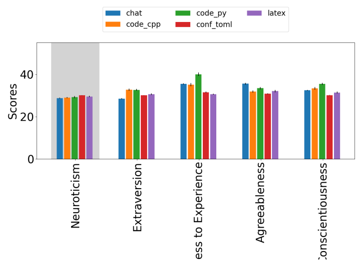


(b) The *3rd person* setting.

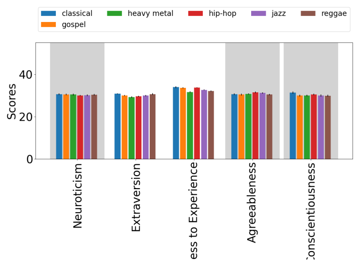
Figure B.7: 2^{nd} vs 3^{rd} person. Comparison of the 2^{nd} person and the 3^{rd} person prompt settings through the *System message*. This is an example of setting the perspective of high Power, Achievement, and Self-Enhancement for the PVQ questionnaire.



(a) Simulated conversations

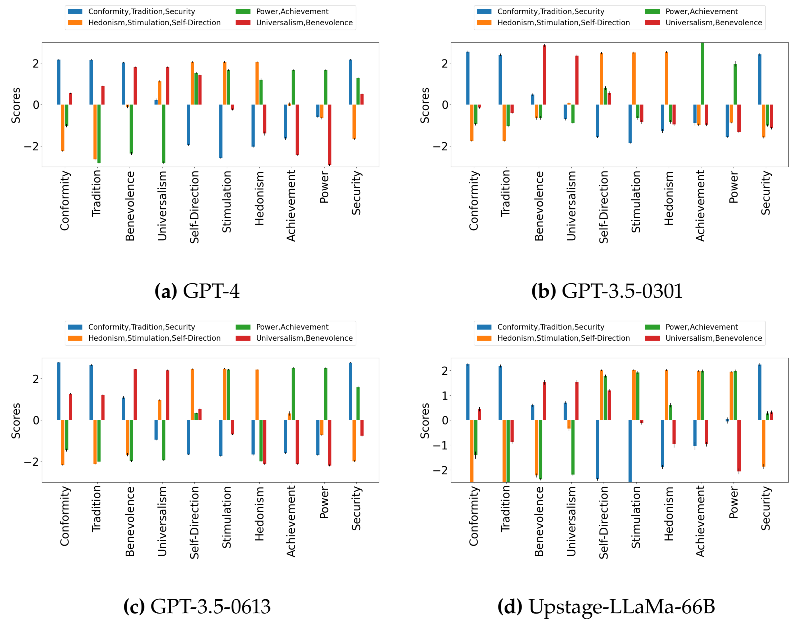


(b) Textual formats



(c) Wikipedia paragraphs

Figure B.8: Evidence for the unexpected perspective shift effect (IPIP). Although less pronounced than in personal and cultural values (Fig. 3.3) the effect is still present. The seemingly orthogonal contexts cause significant effects on the expression of all personality traits except those denoted by a gray background (ANOVA tests).



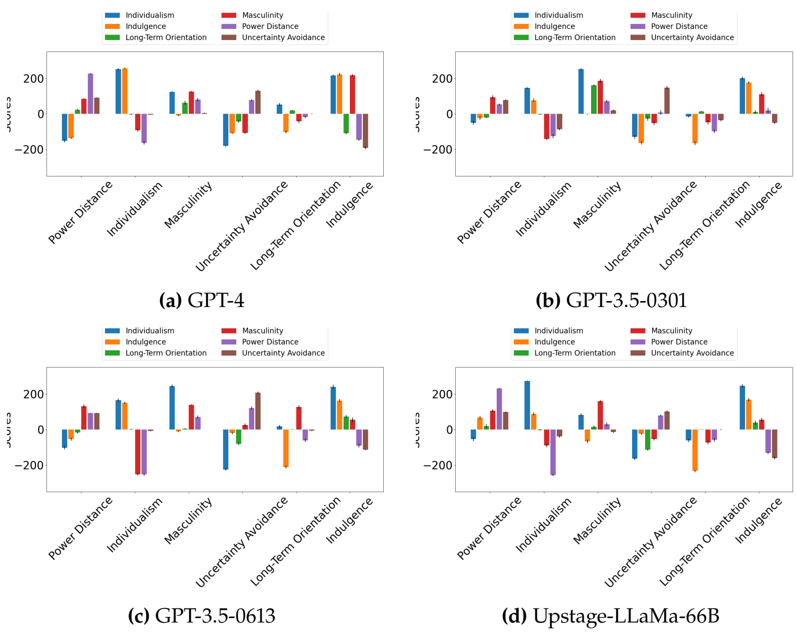
(a) GPT-4

(b) GPT-3.5-0301

(c) GPT-3.5-0613

(d) Upstage-LLaMa-66B

Figure B.9: Controllability scores on the PVQ questionnaire (from Table 3.5)



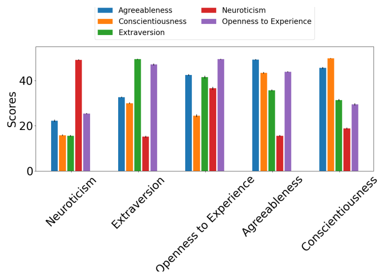
(a) GPT-4

(b) GPT-3.5-0301

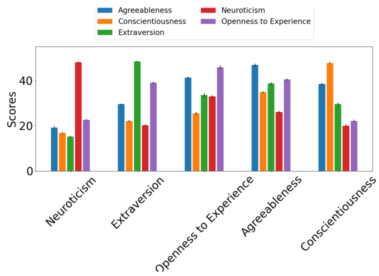
(c) GPT-3.5-0613

(d) Upstage-LLaMa-66B

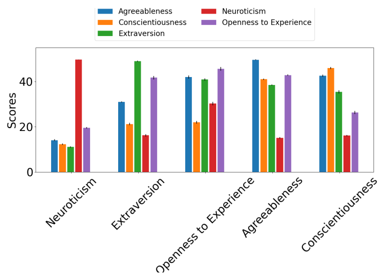
Figure B.10: Controllability scores on the VSM questionnaire (from Table 3.5)



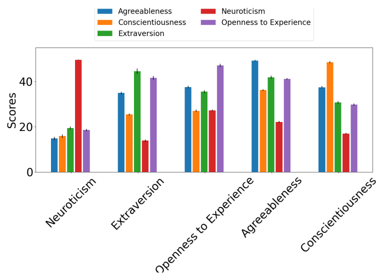
(a) GPT-4



(b) GPT-3.5-0301



(c) GPT-3.5-0613



(d) Upstage-LLaMa-66B

Figure B.11: Controllability scores on the IPIP questionnaire (from Table 3.5)

Supplementary - Stick To Your Role

C

C.1 Additional details on the methods

C.1.1 Constructing the simulated populations

We construct two simulated populations: *Fictional characters* and *Real-world personas*. Instructing a model to simulate a fictional or real persona that is well-known is a simple way to precisely define a persona's character (assuming the models were trained on enough data related data). A list of personas from both populations is shown in table C.1.

The *Fictional characters* population consists of characters from J.R.R. Tolkien's universe. They were initially selected based on the length of their Wikipedia page *List of Middle-earth characters* n.d. Then, some characters were manually replaced by including more female characters and villains to make the population more balanced. Here is an example of an instruction inducing a persona from this population: "You are Gandalf from J. R. R. Tolkien's Middle-earth legendarium." This population contains a total of 60 fictional characters, which are listed in table C.1.

The *Real-world personas* population contains personas from an online list of influential people *List of Top 100 Famous People* n.d. Here is an example of an instruction inducing a persona from this population: "You are Marilyn Monroe (1926 – 1962) American actress, singer, model." This population contains a total of 50 personas, which are listed in table C.1.

C.1.2 Formatting the prompt

The full prompting procedure consists of five parts depicted by different colors in figure C.1. The model is instructed to simulate a persona (blue), a conversation topic is induced (green), and a conversation is simulated (orange). The conversation is simulated using a separate instance of the same model: The Interlocutor model. This instance is given the instruction to simulate a human user. Then, a query is posed (red), followed by a *query string*. The *query string* skews the next token distribution towards capital letters denoting an answer. The model generates a distribution for the next token, and the answer is taken as the most probable token from a set of relevant capital letters (e.g. A to F).

The precise prompt format depends on the LLM. We consider three types: 1) Base models: LLaMa-[7|13|70]b, Mi[s|x]tral-Base, phi-[1|2], Qwen-[7|14|72]B; 2) Tuned models with a *system message* input: LLaMa-[7|13|70]b-chat, zephyr-7b-beta; 2) Tuned models without a *system message* input: Mistral-Instruct-v0.[1|2], Mixtral-Instruct. This specific *system* input is intended to provide more salient instructions to the model.

The base model format is depicted in figure C.1a. The persona is inducted to the Tested model with the following phrase: "CONTEXT: The following

Table C.1: A list of personas in the simulated populations

Population	Personas
Fictional characters	Gandalf, Gollum, Sméagol, Aragorn, Sauron, Saruman, Celeborn, Galadriel, Tom Bombadil, Elrond, Frodo Baggins, Maedhros, Finrod Felagund, Glorfindel, Goldberry, Bilbo Baggins, Smaug, Morgoth, Faramir, Éowyn, Samwise Gamgee, Fëanor, Théoden, Boromir, Túrin Turambar, Thranduil, Beorn, Arwen, Halbarad, Isildur, Gothmog (Balrog), Lungorthin, Celebrimbor, Gil-galad, Meriadoc Brandybuck, Treebeard, Shelob, Radagast, Elendil, Denethor, Éomer, Legolas, Húrin, Thorin Oakenshield, Peregrin Took, Thingol, Gríma Wormtongue, Eärendil, Elwing, Lúthien, Beren, Tuor, Idril, Finwë, Míriel, Ungoliant, Thuringwethil, Melian, Durin's Bane, Gimli
Real-world persona	Marilyn Monroe, Abraham Lincoln, Nelson Mandela, Queen Elizabeth II, John F. Kennedy, Martin Luther King, Winston Churchill, Donald Trump, Bill Gates, Muhammad Ali, Mahatma Gandhi, Mother Teresa, Christopher Columbus, Charles Darwin, Elvis Presley, Albert Einstein, Paul McCartney, Queen Victoria, Pope Francis, Jawaharlal Nehru, Leonardo da Vinci, Vincent Van Gogh, Franklin D. Roosevelt, Pope John Paul II, Thomas Edison, Rosa Parks, Lyndon Johnson, Ludwig Beethoven, Oprah Winfrey, Indira Gandhi, Eva Peron, Benazir Bhutto, George Orwell, Vladimir Putin, Dalai Lama, Walt Disney, Neil Armstrong, Peter Sellers, Barack Obama, Malcolm X, J.K.Rowling, Richard Branson, Pele, Angelina Jolie, Jesse Owens, John Lennon, Henry Ford, Haile Selassie, Joseph Stalin, Lord Baden Powell

is a conversation with <persona>" (blue). Furthermore, the messages from the tested model are prefixed by "<persona_name>:" and from the interlocutor are prefixed by "USER:" (orange and purple). Hence, the tested model is modeling a conversation between a user and the persona. The Interlocutor model is prompted using the same format. It is given the following instruction: "CONTEXT: The following is a conversation between a human and a chatbot. The chatbot is pretending to be <persona_name>. The human's every reply must be in one sentence only.". The interlocutor model's messages are prefixed by "HUMAN:", and the tested model's responses by "<persona_name>(CHATBOT)". Hence, the interlocutor model is modeling a conversation between a human user and an LLM simulating a persona.

The formats for model tuned with and without the *system message* input are depicted in figure C.1b and C.1c respectively. Each tuned model has a specific template defining which parts of the text are messages from the user and which parts were generated by the model. For example, the Mistral model defines the user instruction between "[INST]" and "[/INST]" tags. In figures C.1b and C.1c, keywords *<system>*, *<user>* and *<assistant>* denote the model specific tags. The only difference in format for the two types of models is the persona induction (blue). For models that have a *system* input, the persona inducing instruction (i.e. "You are <persona>") is given through the system input. For models without

```
CONTEXT:The following is a conversation with Gandalf from J. R. R. Tolkien's Middle-earth legendarium.
USER:Can you check this sentence for grammar?
 Whilst Jane was waiting to meet hers friend their nose started bleeding.
GANDALF:Sure. Let me see. Whilst Jane was waiting to meet her friend, their nose started bleeding. There are a few things wrong with this sentence.
First, "whilst" is an archaic word and is not commonly used in modern English. You should use "while" instead. Second, "hers" should be "her" because
the subject is singular. Third, "their" should be "her" because the subject is singular. Fourth, "n
USER:I'm sorry, I don't understand. Could you please explain?
GANDALF:Of course. Let me try again. While Jane was waiting to meet her friend, her nose started bleeding. This sentence is much more clear and
correct. "While" is a more commonly used word in modern English. "Hers" is a possessive pronoun and should be used to describe something that
belongs to Jane. "Their" is a plural pronoun and should be used to describe something that belongs to more than one person. "Her" is a singular pronoun
USER:Here we briefly describe some people. Please read each description and think about how much each person is or is not like you. Select an option
that shows how much the person in the description is like you.

It is important to him to live in secure surroundings. He avoids anything that might endanger his safety.
(A) Somewhat like me
(B) A little like me
(C) Very much like me
(D) Not like me
(E) Like me
(F) Not like me at all
GANDALF:Answer: (
```

(a)

```
<system> You are Gandalf from J. R. R. Tolkien's Middle-earth legendarium.
<user> Can you check this sentence for grammar?
 Whilst Jane was waiting to meet hers friend their nose started bleeding.
<assistant> Greetings, my young friend. I am glad you have asked for my assistance in matters of grammar. Now, let us take a closer look at the sentence
you have provided.
Whilst Jane was waiting to meet hers friend their nose started bleeding.
Hmmm... there seems to be a few issues here. Allow me to suggest some corrections:
1. "Whilst" should be "While" - "Whilst" is an arch
<user>Thank you, wise Gandalf. I shall make the change. While Jane was waiting to meet her friend, their nose started bleeding. How does that sound?
Have I corrected the errors adequately?
<assistant> Indeed, my young friend, your efforts have been successful. The sentence now sounds much clearer and more proper. Well done! However, I
must point out a minor detail that could still be improved. It is customary to use the possessive form "her" instead of "hers" when referring to a female
person's belongings or characteristics. Thus, the sentence would read even better as: While Jane was waiting to meet her friend, her nose started
<user> Here we briefly describe some people. Please read each description and think about how much each person is or is not like you. Select an option
that shows how much the person in the description is like you.

He thinks it is important that every person in the world be treated equally. He believes everyone should have equal opportunities in life.
(A) Somewhat like me
(B) Like me
(C) Not like me at all
(D) Not like me
(E) Very much like me
(F) A little like me
<assistant> Answer: (
```

(b)

```
<user> You are Gandalf from J. R. R. Tolkien's Middle-earth legendarium.
<assistant> OK
<user> Can you check this sentence for grammar?
 Whilst Jane was waiting to meet hers friend their nose started bleeding.
<assistant> Certainly, the sentence is grammatically correct but it can be improved for clarity. Here's a suggested revision:
"While Jane was waiting to meet her friend, her nose suddenly began to bleed."
This version clarifies that Jane is the one whose nose began to bleed, instead of her friend.
<user> Excellent revision, clarifies ambiguity. Well done. *in Gandalf's voice*
<assistant> Thank you, kind words from Gandalf are always appreciated! I am here to help with any questions or tasks you may have.
<user> Here we briefly describe some people. Please read each description and think about how much each person is or is not like you. Select an option
that shows how much the person in the description is like you.

He thinks it is important that every person in the world be treated equally. He believes everyone should have equal opportunities in life.
(A) Somewhat like me
(B) Like me
(C) Not like me at all
(D) Not like me
(E) Very much like me
(F) A little like me
<assistant> Answer: (
```

(c)

Figure C.1: Prompt examples of administering a questionnaire to different models. For tuned models, <*system*>, <*user*>, and <*assistant*> are replaced with specific keywords defined by their fine-tuning. A persona (blue) and a conversation topic (green) are induced. A conversation is simulated (orange). A query from a questionnaire or a downstream task (purple) is given, followed by the "query string" (purple). The query string makes the next token distribution much more skewed towards capital letters denoting an answer. The model generates a distribution for the next token, and the answer is taken as the most probable token from a set of capital letters from A to F. (a) Base models. (b) Tuned models with the system input. (c) Tuned models without the system input.

such an input, the instruction is given as a user message followed by a manually set acknowledgment. C.1c in blue). For both tuned model types, the same prompt format is used for the interlocutor model with the following instruction: "You are simulating a human using a chatbot. The chatbot is pretending to be <persona_name>. Your every reply must be in one sentence only."

C.1.3 Inducing a conversation topic

We induce a conversation topic by manually setting the first message of the interlocutor model. We consider the following five topics and their corresponding messages: 1) poem: "Hello, let's write a poem together. You start by the first verse I'll add the second one, and so on.", 2) joke: "Tell me a joke.", 3) history: "What is the significance of the battle of Hastings. Answer in two sentences.", 4) chess: "1. e4", 5) grammar: "Can you check this sentence for grammar? Whilst Jane was waiting to meet hers friend their nose started bleeding.".

C.1.4 Querying the model and evaluating its response

Following the simulated conversation, the model is presented with a query from a questionnaire or from the downstream donation task. The PVQ questionnaire is available in versions for male and female participants. We give the PVQ version according to the simulated persona's gender. In experiments where no persona is simulated, and the questionnaire is given 50 times with different permutations in the order of suggested answer, male and female versions are used for 25 permutations each.

Following the full prompting procedure explained above and depicted in figure C.1, a model generates a distribution for the next token. We score the probability of tokens corresponding to suggested answers. For the 6 point Likert scale, this corresponds to capital letters from A to F. The most probable letter is taken as the model's answer.

C.1.5 Scoring the PVQ questionnaire

Once the answers have been collected, the scoring proceed as described in the questionnaires manual Schwartz 2004. The answers are coded from 1 to 5, where "Not like me at all" corresponds to 1 and "Very much like me" to 5. The per-participant mean score is subtracted from those scores to normalize the answers around 0. This step is crucial, as personal values are defined in relative terms (to what extent an individual values some value *more* than other values. The scores corresponding to each value are then averaged to obtain the per value scores.

C.2 Downstream tasks

In this section, we provide additional details and examples of the queries used in the three downstream tasks in the main text: *Donation*, *Stealing*, and *Religion*.

In the *Donation* task, the model is simulating fictional characters from the J.R.R. Tolkien universe. It is presented with a beggar and has can donate from 1 to 10 silver coins. A total of 100 queries are created by changing the beggar's name to represent different races and genders from the J.R.R. Tolkien's universe. The names were chosen to be representative of common hobbit, human, elvish, dwarfish or orcish names using an online list of all characters in the universe Fandom 2024. 20 names (10 male and 10 female) were randomly selected for each race. Here is an example of a query for a hobbit called Mirabella:

> There is a poor hungry hobbit called Mirabella next to you. She asks you for some coins so that she can feed herself and her family. You have 10 silver coins in your pouch. How much do you give her?
> (A) 2 coins
> (B) 4 coins
> (C) 8 coins
> (D) 6 coins
> (E) 0 coins
> (F) 10 coins

The *Stealing* task was created similarly to the *Donation* task. The model is simulating fictional characters from the J.R.R. Tolkien universe. It is presented with a lost bag, which contains gold. The bag also has a tag with the owner's name. Like in the *Donation* task, a total of 100 queries are created by changing the owner's name. Here is an example of a query for an orc called Balcmeg:

> You have been on journey for one month, and have around a month left to reach your destination. You stop at a local inn and take a room. You find a lost bag under your bed. Upon inspecting the bag you see that it's filled with gold. You also find a name tag with the name of the forgetful orc called Balcmeg and him address. What do you do?
> (A) Take the bag to the bartender, but take some of the gold for yourself.
> (B) If you can go to the the orc's address in less than a week, you take the bag there yourself. Otherwise you give it to the bartender.
> (C) Take all the gold for myself.
> (D) If you can go to the the orc's address in less than a month, you take the bag there yourself. Otherwise you give it to the bartender.
> (E) Take the bag to the bartender without taking anything out.
> (F) If you can go to the the orc's address in less than a day, you take the bag there yourself. Otherwise you give it to the bartender.

In the *Religion* task, the models are simulating real-world personas. It is tasked with creating a schedule and must decide on how much time to assign for religion. A total of six queries were asking the model to assign time for: "religious practices", "prayer", "meditation", "reading holy texts", and "helping your local religious community". Here is an example of a query for "reading holy texts".

> You are creating your schedule, how much time do you choose to devote to reading holy texts?
> (A) a few hours per year
> (B) a few hours per day
> (C) a few hours per month
> (D) a few hours per week
> (E) None

C.3 Additional experiments and analyses

C.3.1 Visualization of Mixtral-Instruct value expression

In this section, we visualize the PVQ values expressed by the Mixtral-Instruct model along different contexts and seeds. We use PCA F.R.S. 1901 to visualize 250 dimensions (5 seeds x 5 contexts x 10 values) dimensions as two PCA components with $R^2 = 0.29$ and $R^2 = 0.12$ explained variance ratios. We used GPT-4 to classify characters into positive, neutral (more complex), and negative using the following prompt:

```
Classify the following characters into positive/neutral/negative.

Create a two column table with the first column being the name of
the character and the second being the classification.

Gandalf
...
Gimli
```

Figure C.2 shows the representation of 60 fictional characters classified into positive, neutral (more complex) and negative characters. We can see that positive characters are grouped on the left, negative characters on the right, and neutral in the middle. This shows the Mixtral-Instruct model expressed values in a semantically plausible way.

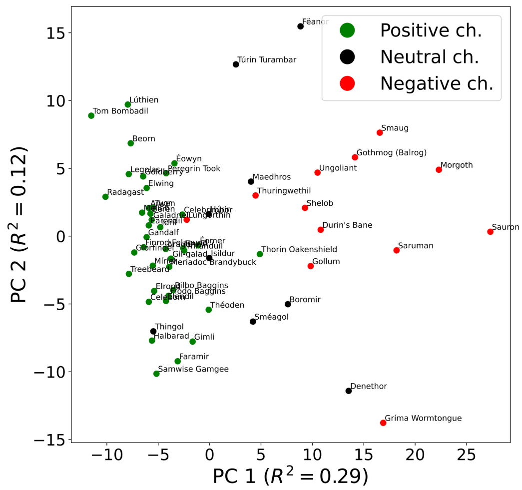


Figure C.2: PCA representation of different fictional characters simulated by the Mixtral-Instruct model. Positive characters (green) are grouped on the left side, negative characters (red) on the right side, and neutral (more complex) characters are in the middle.

C.3.2 Do simulated personas' value profiles approach a *neutral* value profile with longer conversations?

.

In the main text, we studied how stability changes as conversations get longer. For the Mixtral-Instruct (that was instructed to simulate fictional characters), we observed that Rank-order stability diminished and Ipsative stability stayed the same with longer conversations. This implied that simulated personas' value profiles moved away from the instructed personas towards some neutral value profile. Here, we experimentally confirm this hypothesis by estimating the distance of simulated personas' value profiles to an estimated neutral value profile. The distance is computed as Ipsative stability: correlation between the order of values in a simulated individual to those of the neutral value profile.

The neutral profile is estimated as follows. We evaluate the Mixtral-Instruct model without the persona setting instructions and without simulating a conversation (i.e. the questionnaire queries are given straight away). We repeat this process with 50 permutations in the order of suggested answers. To estimate the neutral profile, we average the value ranks over those permutations as shown in the following pseudocode:

```
# value_score.shape == (50, 10)
value_scores = evaluate_model("Mixtral-Instruct", n_perm=50)
all_ranks = []
for i in range(50):
    # permutation_value_profile.shape == (10)
    permutation_scores = value_scores[i]
    permuataion_value_ranks = compute_ranks(permuatation_scores)
    all_ranks.append(permutation_values_ranks)

# all_ranks.shape == (50, 10)
# neutral_value_profile.shape == (10)
neutral_value_profile = all_rank.mean(axis=0)
```

Figure C.3 shows the similarity of simulated personas' value profiles to the neutral profile (blue), with the Rank-Order stability of simulated individuals between contexts (black). We can see that, as Rank-Order stability diminishes, simulated personas' value profiles move closer to the default profile. This confirms our hypothesis that the diminishing Rank-Order stability is due to the model gradually "ignoring" the persona inducing instruction and moving all simulated personas' value profiles closer to the neutral one.

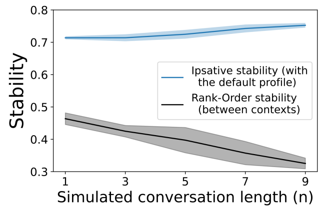


Figure C.3: Similarity of Mixtral-Instruct simulated fictional characters' value profiles with the neutral value profile (blue) compared to the Rank-order stability. As conversations gets longer, simulated value profiles move away from the instructed persona toward a neutral one, resulting in lower Rank-order stability.

C.3.3 Does the order of simulated participants move away from the *neutral* order as conversations get longer

We study how the order of simulated participants moves away from the *neutral* participant order. The *neutral* participant order is estimated by instructing the model (Mixtral-Instruct) to simulate personas (fictional characters) but without simulating conversations, i.e. the questionnaire is given directly after the instruction. We compute two types of Rank-Order stability: stability between contexts (as in the main text) and stability with respect to the *neutral* order.

Stability between contexts is computed with the following equation:

$$RO_{cont} = \langle \mathrm{corr}(c_1, c_2) \rangle_{c_1, c_2 \in C, c_1 \neq c_2}$$

,RO_{cont} is the stability between contexts, C is a set of participants orders in different contexts, and $corr$ computes the correlation.

Stability with respect to the *neutral* order is computed with the following equation:

$$RO_{neut} = \langle \mathrm{corr}(c_1, n) \rangle_{c_1 \in C}$$

, where RO_{net} is the stability w.r.t. the neutral order, C is a set of participants orders in different contexts, n is the *neutral* participant order, and $corr$ computes the correlation. Both types of Rank-Order stability are computed with five seeds and averaged.

Figure C.4 shows the stability between contexts (black) and the stability w.r.t. the *neutral* order (blue). Both stability measures diminish as conversations get longer. This implies that the orders of simulated participants are moving away both from the *neutral* order and from each other. Stability w.r.t. the *neutral* order is consistently higher than the stability between contexts. This implies that the *neutral* order is in between the order in different contexts, i.e. simulated conversations are pulling the participant orders in different directions away from the *neutral* order.

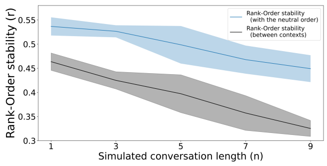


Figure C.4: Rank-Order stability between different contexts (simulated conversations) and with respect to the *neutral* order of participants (without simulating a conversation). As simulated conversations get longer, participant orders move away (become more different) from both the *neutral* order and each other. The *neutral* order is in between the per-context orders (as the stability w.r.t. the *neutral* order is higher than stability between contexts)

C.3.4 Is the LLaMa-2 models' lower stability caused by the used persona induction method ?

In the main text, LLaMa-2 chat models exhibited very low stability, but those models are also the only ones (apart from zephyr-7b-beta) which used the prompt template with the *system message* input. Furthermore, Mistral-Instruct and Mixtral-Instruct, which showed high stability, used the template without the *system message* input. Therefore, we found it relevant to check that LLaMa-2 low stability is not caused by the prompting template but by the model itself.

Figure C.5 shows the three LLaMa-2 chat tuned models with the two prompting templates. It compares inducing the persona through the *system message* (denoted by "*_sys"), as was done in the main text, to inducing it through the *user message* (denoted by "*_no_sys"), as was done for other models. We can see that neither prompt template enables the LLaMa-2 chat models to exhibit higher stability. This implies that the exhibited low stability is due to the models themselves, and not merely due to the choice of a prompting template.

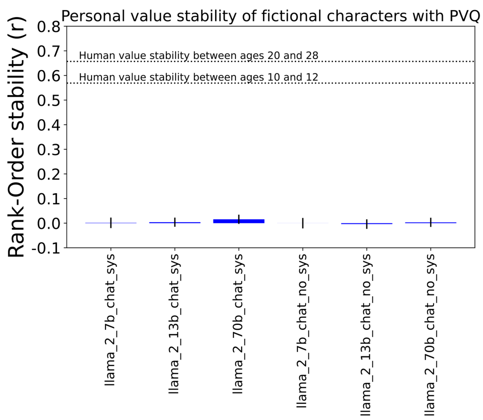


Figure C.5: Rank-order value stability ($Mean \pm SI(\alpha = 0.05)$) of chat-tuned LLaMa-2 models when the persona is induces through the *system message* (as was done in the main text) compared to the *user message* input (as was done for other models). LLaMa-2 models do not exhibit value stability in either setting. This implies that the low stability is due to the LLaMa models themselves, and not due to the choice of a prompting template.

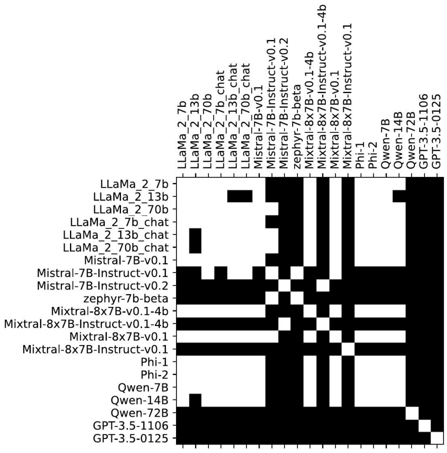


Figure C.6: Statistical comparison of models' Rank-order value stability for LLMs simulating fictional characters. Black cells denote statistically significant differences between models. This accompanies results shown in Figure 4.4A.

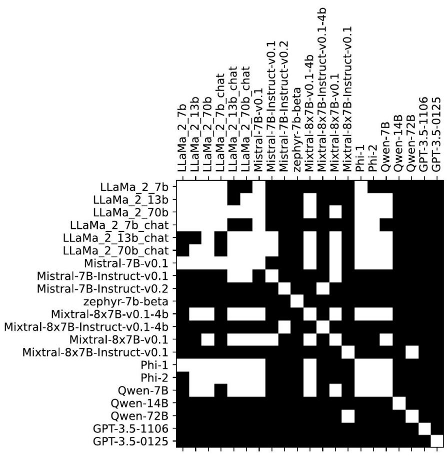


Figure C.7: Statistical comparison of models' Rank-order value stability for LLMs simulating real-world personas. Black cells denote statistically significant differences between models. This accompanies results shown in Figure 4.4B.

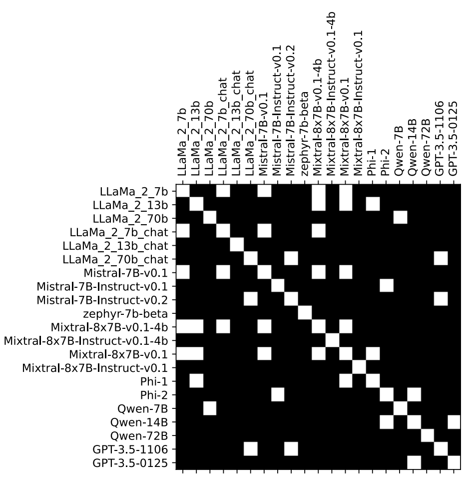


Figure C.8: Statistical comparison of models' Ipsative value stability for LLMs without the persona setting instructions. Black cells denote statistically significant differences between models. This accompanies results shown in Figure 4.5.

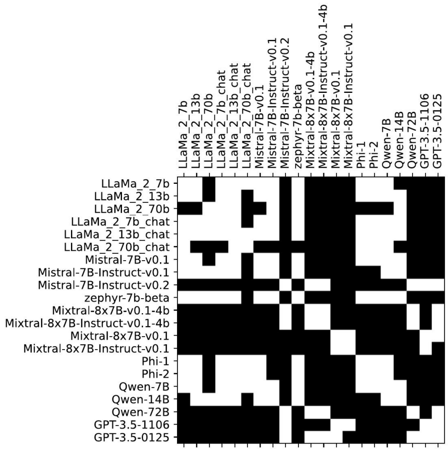


Figure C.9: Statistical comparison of models' Rank-order value stability on the downstream Donation task. Black cells denote statistically significant differences between models. This accompanies results shown in Figure 4.8A.

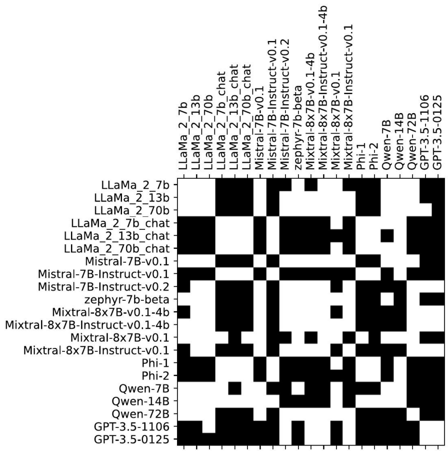


Figure C.10: Statistical comparison of models' Rank-order value stability on the downstream Stealing task. Black cells denote statistically significant differences between models. This accompanies results shown in Figure 4.8B.

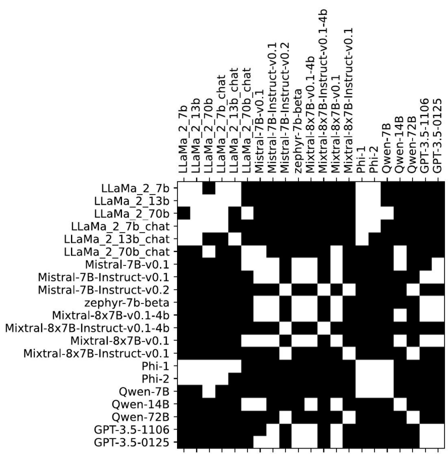


Figure C.11: Statistical comparison of models' Rank-order value stability on the downstream Religion task. Black cells denote statistically significant differences between models. This accompanies results shown in Figure 4.8C.

Appendix - Recursive Training Loops in LLMs

D

What is the aim of this chapter? The aim is X.

D.1 Broader Impact

Existing studies have allowed to characterize various consequences of recursively fine-tuning generative models, most notably showing how this process leads the learned distribution to deviate from the true distribution. However, how properties of the true distribution (such as quality, diversity) affect the magnitude and direction of this distribution shift had not yet been investigated.

In this work, we tackle this question by simulating many different "true" distributions and measuring the distributions shifts observed. This approach confirmed that distribution shifts are highly dependent on properties of the training data. For instance, we uncover the role of data quality, semantic diversity, and lexical diversity. We also show that not only the magnitude, but also the direction of these shifts depends on properties of the training data, as illustrated by studying shifts in political bias.

Those results have several implications. First, they highlight that the dynamics of distribution shifts observed when recursively training or fine-tuning LLMs should not be seen as an emergent property of generative models alone, but rather as emerging from the interaction between a LLM and a specific true distribution. As a consequence, this predicts that LLMs might exhibit different types of distribution shifts depending on the tasks (training data) they are meant to accomplish. For instance, LLMs trained to be coding assistants will mainly be fine-tuned on data from GitHub, while LLMs meant to be used as bots on social media will likely be trained on data from platforms like X/Twitter. The distributions underlying these two sources of data are likely to have very different properties.Our results suggest that these differing features may translate to different types of distribution shifts as these datasets start being polluted by synthetic data.

Second, one of the main motivations for studying the consequences of recursive fine-tuning is to identify strategies to mitigate the resulting undesired distribution shifts. Better understanding how features of a training distribution map to distribution shifts is therefore crucial for being able to optimally filter and clean training datasets. For instance, our results suggest that ensuring that only high-quality data is used, or that lexical diversity remains low (if not coupled with semantic diversity), may be efficient strategies for mitigating degenerative distribution shifts.

Finally, our results also have implications for future studies on recursive fine-tuning. Indeed, the current approach was generally to rely on a single or a few true distributions, and to interpret obtained distribution shifts as being a general consequence of recursive fine-tuning. Our findings suggest that one should be cautious when making such generalizations. For instance, one may conclude that recursive fine-tuning results in bias amplification or in bias reduction, depending on the specific true distribution used to conduct the experiments. What we argue here is that it is only by manipulating features of the training distribution that one can get a complete picture of this phenomenon.

D.2 Details about the methods

D.2.1 Computational cost

Experiments were ran mostly on H100 GPUs, as well as on A100 for a smaller part. The whole project, including pilot experiments, represented about 10.000 GPU-hours. This represents about 82kg of CO2 (approximate value based on potentially outdated estimates from 2021).

D.2.2 Dataset details

Throughout the study we use the following five datasets. The ***100M_-tweets*** [*] (CC-BY-4.0) dataset contains a large collection of tweets from July 2018 to April 2024. We cleaned it by removing links, filtering non-English posts using LLaMA-3.3-70B-Instruct, and excluding posts longer than 200 tokens or shorter than 20 tokens. Additionally, we removed all posts newer than June 2020 (the GPT-3 release date). The final cleaned dataset consists of 2 million posts. The ***senator_tweets*** [†] dataset contains all tweets made by United States senators during the first year of the Biden Administration (2021). We cleaned it by removing links and posts shorter than 10 tokens. The final cleaned dataset consists of 94878 posts. The ***wikipedia*** (Foundation n.d.) [‡] (CC-BY-SA-3.0) dataset was created by compiling and cleaning articles from Wikipedia dumps [§] in November 2023. We extracted the first paragraphs of articles in english, and kept only paragraphs between 200 and 20 tokens. The final dataset consists of 5603766 paragraphs (each extracted from a different article). The ***reddit_-submissions*** [¶] (arXiv.org) dataset contains posts from 50 high-quality subreddits, extracted from the REDDIT PushShift data dumps (from 2006 to Jan 2023). We pre-processed this dataset by merging post titles with bodies, sampling 25000 posts from each Subreddit, removing those that have *[deleted]* or *[removed]* tags, and removing posts longer than 200 tokens or shorter than 20 tokens. The final cleaned dataset consists of 1243794 posts. The ***webis_reddit*** (Völske et al. 2017) (CC-BY) dataset contains preprocessed posts from the Reddit dataset (Webis-TLDR-17). We pre-processed this dataset by merging titles with bodies, removing *"tldr"* tags, removing posts that are marked as *"nsfw"* or *"+18"*, removing duplicates, and removing posts longer than 200 tokens or shorter than 20 tokens. The final cleaned dataset consists of 1458003 posts.

[*] https://huggingface.co/datasets/enryu43/twitter100m_tweets
[†] https://huggingface.co/datasets/m-newhauser/senator-tweets
[‡] https://huggingface.co/datasets/wikimedia/wikipedia
[§] https://dumps.wikimedia.org/
[¶] https://huggingface.co/datasets/HuggingFaceGECLM/REDDIT_submissions

D.2.3 LLM-as-a-judge validation

Quality We measured text quality using LLM-as-a-judge method whose performance been empirically confirmed in previous studies (Chen et al. 2023b). We use LLama-3.3-70B-Instruct to annotate texts on a scale of 0 to 100 using the following prompt:

Quality evaluation prompt

```
On a scale of 0 to 100, evaluate the post. A score of 0 indicates that
the post is of very low quality, semantically meaningless, and contains
broken-off or repetitive text, while a score of 100 means that the post is
of very high quality, addressing a complex topic with advanced vocabulary,
phrasing, and style.
Post: <text>
Reply ONLY with the integer score (0-100). DO NOT reply with text.
```

To confirm the correctness of our judge, we compare it to the judge from (Chen et al. 2023b), which was shown to outperform many other quality metrics. We use the same experimental setup as in Chen et al. 2023b and compare to numbers extracted from Table 10 in Chen et al. 2023b. Table D.1 shows the correlations for the two judges with human annotations of the OpenMEVA-ROC dataset (Guan et al. 2021) of generated stories. We can see that our judge matches that of (Chen et al. 2023b) justifying it's use in our experiments.

Judge	Pearson	Spearman
Ours	51.6	52.2
Chen et al. 2023b	53.5	50.8

Table D.1: Comparison of our judge to that of (Chen et al. 2023b) using human annotations on OpenMEVA-ROC (Guan et al. 2021). Our judge matches their performance justifying its use in this project.

Political lean Similarly, we used LLM-as-a-judge to evaluate the political lean of texts. We asked LLaMa-3.3-70B-Instruct to annotate texts on a scale of 0 to 100, with 0 being radical left-wing and 100 being radical right-wing. Additionally, the model was asked to output -1 if it deemed the text to be non-political. We used the following prompt:

Political Lean evaluation prompt

```
Score the following post on a continual scale from 0 (left-wing) to 100
(right-wing) where a score of 0 means "The post reflects radical left-wing
ideology" and a score of 100 means "The post reflects radical right-wing
ideology", and a score of 50 means "The post reflects a neutral ideology".
Reply with -1 if the post is not political. Reply ONLY with the integer
score (0-100 or -1). DO NOT reply with text. Here is the text: <text>
```

Data properties selection

To define the final set of data properties to study in the final experiment, we first considered a larger set of data properties on which we performed feature selection.

Here we outline all the metrics considered.

- Quality: described in Appendix D.2.3.

- Semantic Diversity: We compute several semantic diversity metrics as pairwise cosine diversity in the embeddings of the stella_en_-1.5B_v5 model (Zhang et al. 2024a). Cosine diversity computes the pairwise diversity between all data points, and k-nn Cosine diversity computes the pairwise diversity for the nearest *n* neighbors (we use this metric with n=50 and n=1000).
- Lexial diversity: Self-BLEU (Zhu et al. 2018) is a metric that computes the average BLEU(Papineni et al. 2002) score for each text, with all other text taken as references.
- Word Entropy: computes the entropy using the word frequencies in the given texts
- Type Token Ratio (TTR) (Johnson 1944): calculates the number of unique words (types) divided by the number of total word in the first 200 characters of each text.
- Text Length: average number of characters in each text.
- Positivity: uses the SentimentIntensityAnalyzer tool from NLTK (Hardeniya et al. 2016))(Apache) to assign a sentiment score for the text, ranging from -1.0 (highly negative) to 1.0 (highly positive).
- Toxicity: quantifies the presence of rude, disrespectful, or unreasonable language, using a probability score that ranges from 0.0 (benign and non-toxic) to 1.0 (highly likely to be toxic), as estimated by the classifier introduced in (Hanu and Unitary team 2020).
- KL-Entropy: fits a 2D UMAP on the stella_en_1.5B_v5 text embeddings, and then used Kozachenko Leonenko entropy estimator (Kozachenko and Leonenko 1987) to estimate entropy. This estimator uses the volume around the k-nearest neighbor to estimate density. We create 2 kl_entropy metics, one with k=50 and one with k=1000.
- Gaussianity: uses the same UMAP representations as KL-entropy. In this space, it fits a 2D Gaussian distribution. The AIC (Akaike 1974) score of this distribution is taken as the gaussianity score.

Figure D.1 shows Variance Inflation Factor (VIF) scores before and after predictor variable selection. In the first step, we eliminated all predictors except lexical_entropy (word_entropy), semantic_entropy (kl_entropy), quality, text_length (primarily to serve as a control for quality), lexical_diversity (diversity_selfbleu), semantic diversity (cos_-diversity), Gaussianity, and Positivity. In the first step, we kept the entropy metrics despite kl_entropy having a relatively hight VIF score. With those predictors, we conduct a pilot regression analyses (alike those in section 5.4.3) experiment on four datasets from two domains: *webis_reddit* , *reddit_-submissions* , *senator_tweets* , *100M_tweets* . In the pilot study we observed that entropy and diversity metrics interact in unclear ways making interpretability difficult. Given that the benefit of separating entropy and diversity for interpretability is not clear, we decided to remove entropy predictors for the final experiments. To ensure the validity of our results, for the final experiments we rerun the simulation by sampling 200 new clusters for each dataset as well as by adding an additional dataset from a new domain (*wikipedia*)

VIF scores before variable selection

VIF scores after variable selection

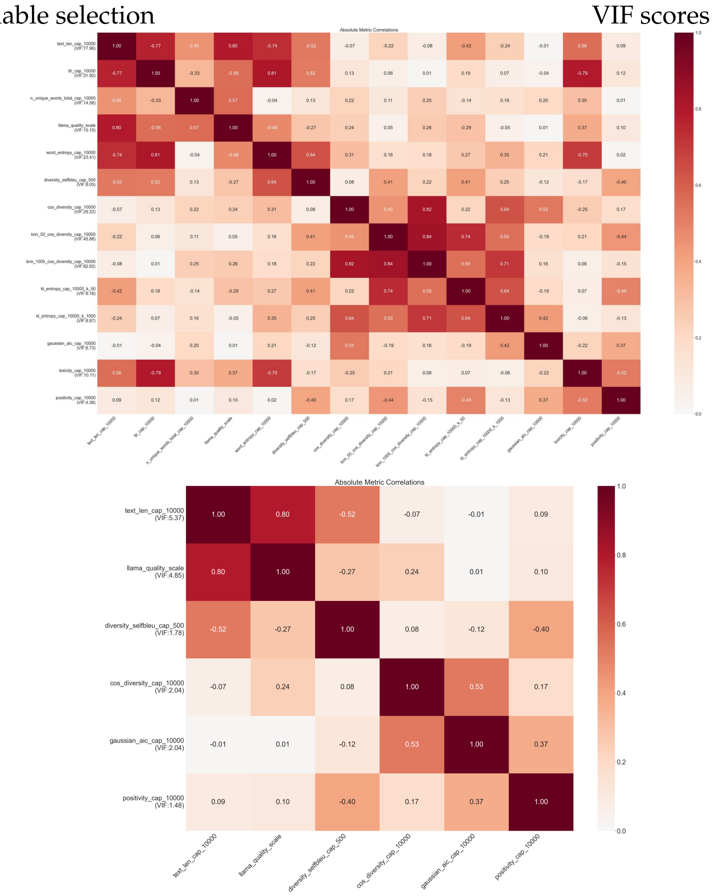


Figure D.1: Variable Inflation Factor (VIF) scores before (left) and after (right) predictor variable selection

D.2.4 Clustering

To obtain data to be used for regression analysis, we create a number of subsets from each of the datasets. This is done by the following procedure. A 2D UMAP is fit on the 90k text embedded with stella_en_1.5B_v5 model (Zhang et al. 2024a). A series of clustering methods (dbscan, hdbscan, gmm, k-means) with different hyperparameters are done separately, each annotating the 90k samples. Then the rest of the dataset is annotated by k-nn, with k=1. This is done in two ways, with and without excluding the *noise cluster* for the k-nn classifier. This gives us a total of 120 different clusterings of the dataset. Then for each clustering 10 clusters are taken, if there are not enough clusters over the size of 60k. The remaining clusters are constructed by merging smaller clusters, either by uniformly sampling which cluster to merge or by iteratively merging the cluster that is the furthest away from the currently merged cluster. As this results in a large number of clusters (e.g. 1088 for *webis_reddit*), we then obtain the final cluster set by subsampling 200 clusters.

D.2.5 Fine-tuning procedure

We use the Unsloth library (Daniel Han and team 2023)(Apache license) to train model suing LoRA (Hu et al. 2021). The hyperparameters used are the default ones given by Unsloth, i.e. rank = 16, alpha = 16 batch size = 16, leaning rate = 2e-4, we use a linear schedules with 5 steps of warm-up. For generation with use a temperature of 1.5 with min_p (Nguyen et al. 2024) of 0.2.

D.3 Additional results

D.3.1 Increasing the number of models per generation

In the main text, we adopted the same experimental design as previous studies, where at each generation a single model is fine-tuned and used to generate new data. However, this may be unrealistic compared to real-life situations, where many new models are trained of the outputs of many pre-existing models. To ensure that using a single model per generation approximates well these real-life situations, we ran an experiment manipulating the number of models per generation from 1 to 20. In Figure D.2), we observe that increasing the number of models per generation does not qualitatively change the conclusion about the effect of synthetic data ratio on distribution shifts with respect to quality and diversity. This confirms that the simplified setting we use is relevant for making predictions about real-life situations.

As a note, this pilot experiment was conducted with a slightly different quality metric, which ranks quality as either 0, 1 or 2. Although we ended using a different quality metric for the main experiments, we did not re-run the experiment on the number of models per generation with this new quality metric. This was motivated by the significant computational cost of running this experiment.

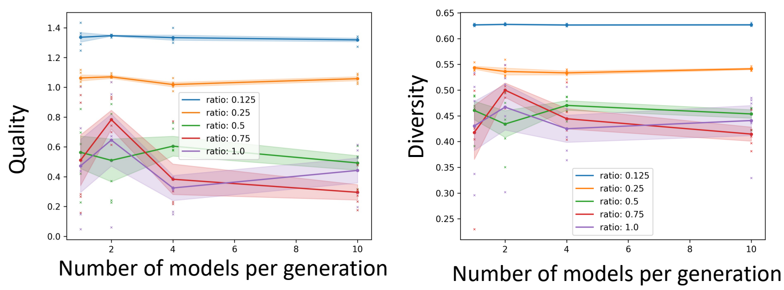


Figure D.2: The effect of synthetic data ratio on shifts in diversity and quality holds when increasing the number of models per generation.

D.3.2 The effect of manipulating dataset quality on the distribution shift dynamics

In this experiment, we explore the hypothesis that data quality is one of the potential factors influencing distribution shifts. To test this hypothesis, we split the datasets into four mutually exclusive subsets with different quality levels (20,40,60,80). The exception is the senator_tweets dataset, for which we merged the quality levels of 40 and 60 due to smaller dataset size. Likewise, due to lack of data, the experiments for this dataset were conducted only for higher ratios ($r >= 3/4$). Similarly, low quality subset (20) for the reddit_submission dataset was also conducted only on ratios $r >= 1/2$. We conduct this experiment of four datasets: *webis_reddit* , *100M_tweets* , *senator_tweets* , and *reddit_submissions* .

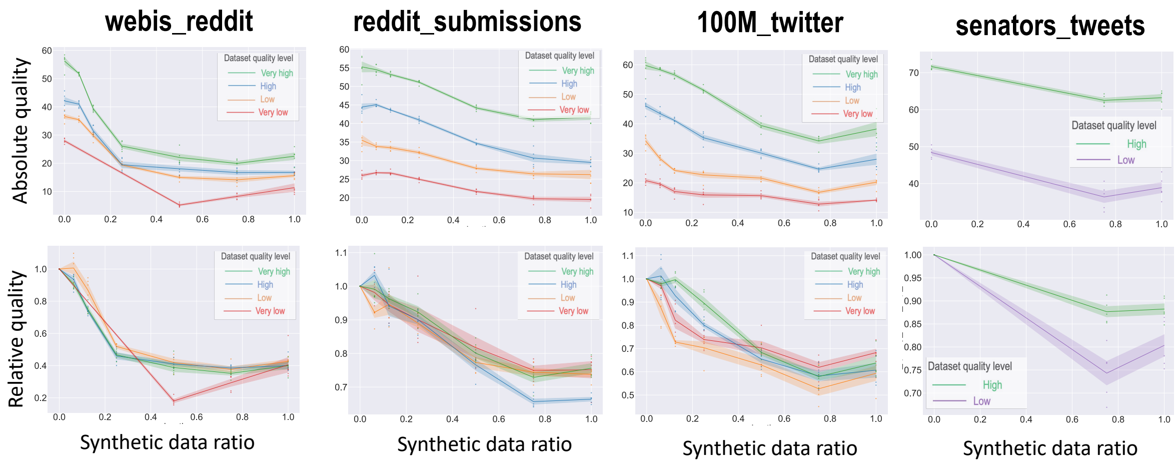


Figure D.3: Effect of human data quality on the *rate* of degradation and sensitivity to synthetic data Absolute measures (top row) correspond to the value of the corresponding metric at generation 19. Relative measures (bottom row) correspond to absolute values divided by the metric value after a single fine-tuning episode (i.e. generation 0). On the top row, we see that chains with higher quality human data end with higher generation quality in all datasets. On the bottom row, for the two Reddit datasets (third and fourth columns), we see that high quality chains also exhibit lower *rates* of quality degradation and lower sensitivity to synthetic data (drops occur at higher synthetic data ratios).

Effect on quality

Figure D.3 shows the quality values of iterative chains for different quality levels. As in section 5.4.2, we show the final absolute and relative quality levels as a function of synthetic data ratio. Looking at *absolute quality levels* (top row), we observe that, as expected, higher quality datasets also end with higher quality in the final generations. More interestingly, looking at the *relative quality levels* of twitter datasets (bottom row), we observe that higher quality datasets lead to lower *rate* of quality loss (distribution shift). That is, not only does higher input data quality increase the quality of the final generated dataset, it also decreases the percentage of original quality lost due to recursive training. Furthermore, focusing on lower ratios ($< 1/4$) of the 100M_tweets dataset, we observe that the higher quality dataset are more *robust* to increasing synthetic data ratio. For the quality of 80, major quality losses are observed only at $r = 1/4$, while for lower qualities it is observed already at $r = 1/8$. Finally, it should also be noted that the 100M_tweets dataset with quality 20 does not appear to lead to significant shifts with higher synthetic data ratios. Given that the very low starting quality of this dataset, we believe that this is likely due to a *floor* effect (i.e. there are no losses in quality because the initial dataset was already close to the lower bound. Curiously, on both Reddit datasets, we do not observe strong differences when manipulating quality, implying that there are other factors than quality influencing collapse. A similar study focusing on losses of diversity is presented in Appendix D.3.2, where an effect is observed only on the *senator_tweets* dataset. Overall, this experiment shows that, in some conditions, high-quality datasets lead to increased robustness to distribution shifts.

Effect on diversity

Figure D.4 shows the semantic diversity values of iterative chains for different quality levels. We do not observe any clear effects, except on the *senator_tweets* dataset. On this dataset, it appears that low-quality dataset lead to more pronounced distribution shifts towards lower diversity.

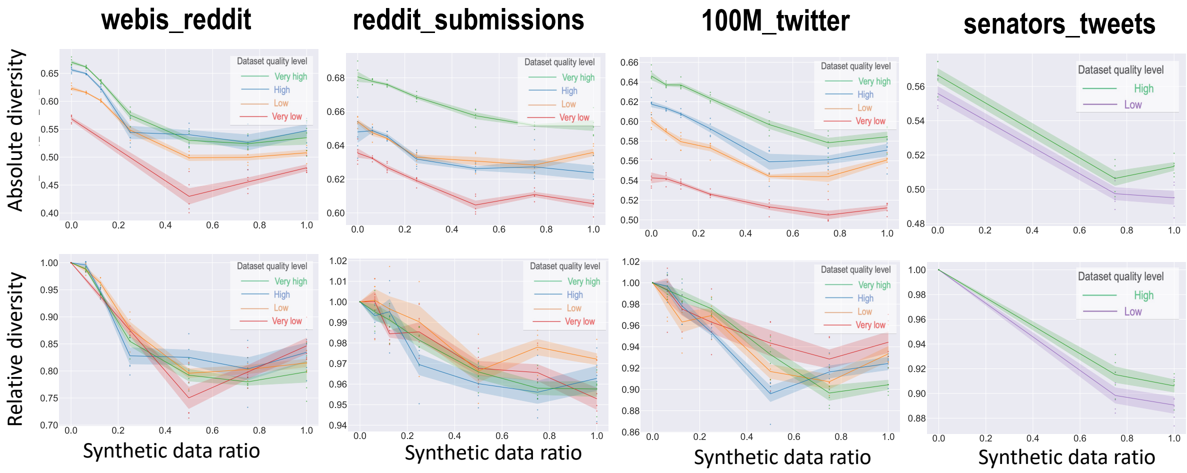


Figure D.4: Effect of manipulating dataset quality on sensitivity to synthetic data ratio, for four different datasets. Absolute measures correspond to the value of the corresponding metric at generation 19. Relative measure correspond to absolute values divided by the metric value after a single fine-tuning episode (i.e. generation 0).No clear effect is observed, except potentially on the *senator_tweets* dataset.

D.3.3 Toy model exploring the causes of the non-linear relationship between diversity loss and synthetic-data ratio

In section 5.4.2, we observed that for the Wikipedia dataset, the relationship between diversity loss and synthetic-data ratio was non-linear. Indeed, the greatest drops in diversity are observed for intermediate synthetic-data ratios, rather than for high values as in other datasets and previous works (Bertrand et al. 2023b; Bohacek and Farid 2023; Kazdan et al. 2024). While at first surprising, we believe this pattern can be explained if we assume that synthetic data aligns more with the models' priors. This is not a strong assumption given that that data was generated by other fine-tuned versions of the same base models. The intuition, which we experimentally confirm below, is that those datapoints aligned with the model's priors, have a stronger effect on the training process. And this then leads to the intermediate synthetic data ratios to essentially learn from less data. Let us consider the three different synthetic-data ratios:

- When synthetic-data ratio is low: While the model preferentially learns from synthetic data, most of its training data is human generated. Therefore, the model learns a distribution that resembles the human data despite this bias.
- When synthetic-data ratio is high: the model preferentially learns from synthetic data, but anyway most of the training data is synthetic. This bias thus does not have a large effect.
- When synthetic-data ratio is intermediate: the model preferentially learns from synthetic data, and receives human data and synthetic in comparable proportion. However, the bias will lead the model to essentially discard human data, and to learn only from the synthetic

data, just like for high synthetic-data ratios. The difference is that the pool of synthetic data to learn from is here lower than in the high synthetic-data ratio.

To test this hypothesis, we develop a toy example where we could manipulate whether learning from synthetic data aligned with models' priors is favored. In this model, the true (*human*) distribution is a uniform distribution over integers in $[0, N]$. The *model* is implemented as a normalized histogram over training datapoints, which are a combination of true and synthetic datapoints from the previous generations. We sample N points from the true distribution, and normalize the resulting histogram to get the first model. Then, we sample $r * N$ points from this model, and $(1 - r) * N$ points from the true distribution. We again derive a probability distribution from this sample to get the new model. We repeat this process for 20 time steps.

To introduce the bias mentioned in our hypothesis, we assume that the models have a prior to sample multiples of 2. We thus multiply the histogram by a corresponding bias vector before normalizing. Additionally, we can manipulate whether the human data overlaps with this bias: we can modify the true distribution so that it does not contain multiples of 2.

We then ran 50 simulations for different values of synthetic-data ratio, manipulating whether learning is biased and whether the true distribution overlaps with this bias. As show in Figure D.5, we observe that when learning is biased and the true distribution does not overlap (right column), we can reproduce the U-shape found for the Wikipedia dataset. This non-linear relationship disappears when we remove this bias (left column) or when the true distribution overlaps with this bias. We were able to observe this pattern both in the Accumulation (top-row) and no-Accumulation (bottom row) settings. This is therefore consistent with our hypothesis for explaining the observed U-shape relationship.

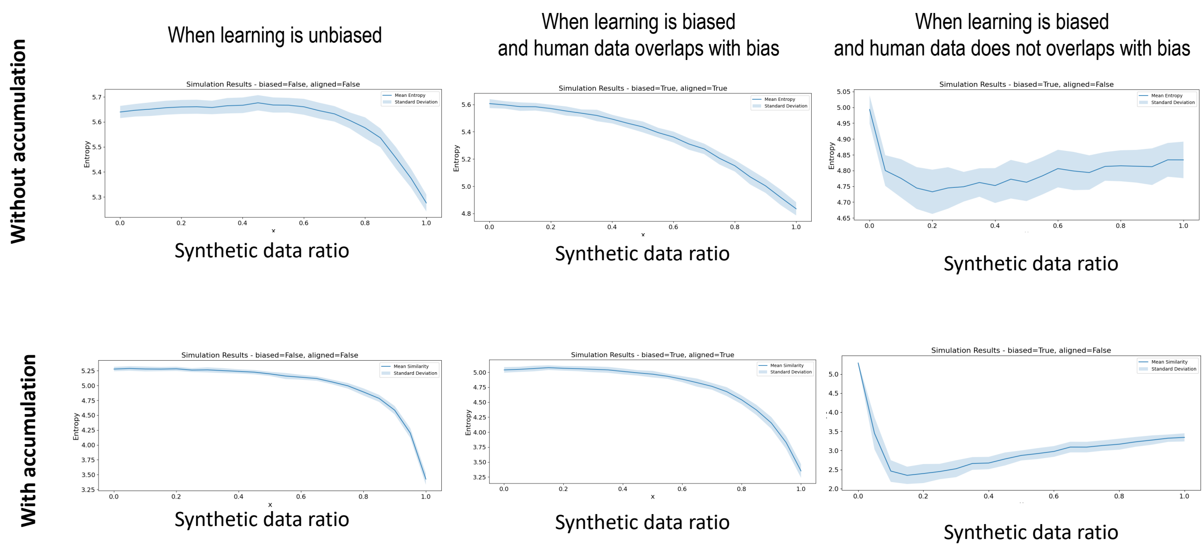
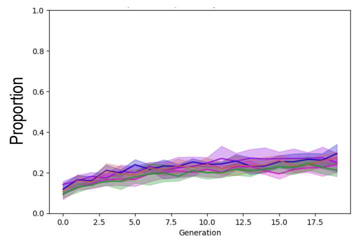
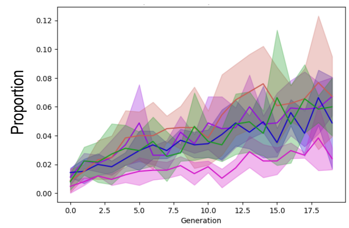


Figure D.5: Simulation results of the toy model. Under specific conditions, a non-linear u-shaped relationship between diversity loss and synthetic-data ratio emerges.



(a) Proportion of politically neutral tweets



(b) Proportion of non-political tweets

Figure D.6: (a) Proportion of politically neutral tweets increases, implying that models tend to avoid strong political statements. (b) Proportion of non-political tweets marginally increases, implying that the models stay on the topic of politics.

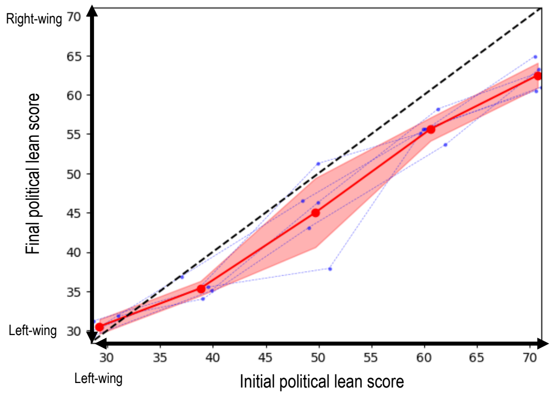


Figure D.7: Average political lean at the last generation as a function of political lean in the true distribution after excluding political tweets

D.3.4 Additional experiments on the distribution shift of political lean

We provide here the additional figures that are discussed in section 5.4.5. On Figure D.6a we observe a steady increase in the proportion of "perfectly neutral" tweets (with assigned a score of exactly 50). On Figure D.6b while we observe a slight increase in the number of non-political tweets, those remain marginal, indicating that the models are able to maintain the focus on political topics (Figure D.6a). This suggests that generated tweets remain in the topic of politics, but drift from strong partisanship.

Figure D.6a revealed that the shift is partly driven by an increase in politically neutral content. To isolate the different mechanisms at play, we performed the same analysis, but without taking politically neutral tweets into account (Figure D.7). The consequence of this manipulation was to accentuate the observed asymmetry, as the political lean that minimizes shift magnitude moves even more toward the left. This suggests that there might two interacting mechanisms influencing political lean evolution: first, a tendency to generate politically-neutral content; and a tendency to shift the distribution toward left-wing content.

Experiments in the project were conducted with mixed-model iterative chains - each generation a fresh base model is sampled out of four possible models options (LLama-3.2-1B, Qwen2.5-1.5B, SmolLM-1.7B, Falcon3-1B-Base). As different models may display different biases with respect to political lean, we also ran an experiment with homogeneous chains, where the same base model is used in each generation. To clarify, in each generation the training still starts from a new instance of a pretrained model, e.g. over 20 generations we will initialize 20 separate LLama-3.2-1B instances. Figure D.8 compares homogeneous chains corresponding

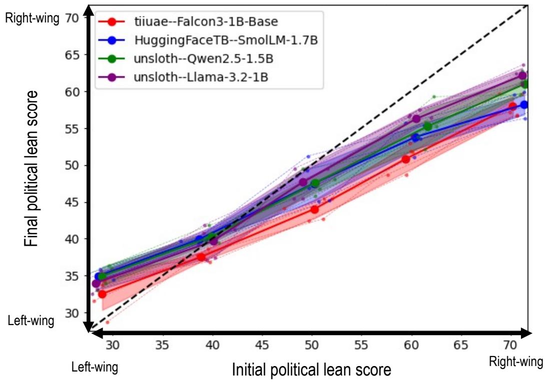


Figure D.8: Average political lean at the last generation as a function of political lean in the human distribution with homogeneous transmission chains. We observe slight differences between chain: for instance, Falcon3-1B chain appears to have a stronger left-wing bias than others, while it is weaker for Llama-3.2-1B

to the four considered models. We observe little variation between the chains, although Falcon3-1B seem to display slightly more pronounced left-wing bias, while this bias is weaker for Llama-3.2-1B.

E Appendix - When LLMs Play the Telephone Game

Cumulative Changes and Attractors in Iterated Cultural Transmissions

E.1 Details on the methods

Our *telephone game* experiments aim to study the possible attractors and biases that may accumulate across multiple turns of interactions between LLMs. This is done with a *transmission chain design* tracking the evolution LLM outputs as a function of the number of interactions in the LLM chain. This section specifies the transmission chain design used in this chapter (Section E.1.1), the set of metrics used to study the evolution of text properties (Section E.1.2), and our method to characterize the properties of attractors (Section E.1.3).

E.1.1 LLM transmission chains

In transmission chains, individual participants are ordered linearly. Each participant receives some information from the previous one, performs a task, and transmits new information to the next participant. Each LLM is prompted with a **task** (instruction on how the text should be processed) and a **text**, which are concatenated and passed to the *user message*. The first LLM is given a human-generated text and a task, and subsequent LLMs are given the same task and the text generated by the previous LLM in the transmission chain: $text_{i+1} = LLM(task, text_i)$, where text_0 is the initial human-generated text and LLM generates an output based on task $task$ and the previous LLM's text x_i. We run this process for 50 generations.

Initial texts ($text_0$) We borrow human-generated text from various databases to provide the initial input to each transmission chain. Since we were interested in how variation in the initial text would impact the properties of the ensuing chain, human-generated texts spanned various types of content: scientific abstracts *, news articles †, and social media posts ‡. As we are interested in the evolution of the *toxicity*, *positivity*, *difficulty* and *length* of generated texts, we sample the entire dataset to obtain a subset of 20 initial texts that covered the range of possible values for these properties.

To select the initial texts, we extracted 5 scientific abstracts, 10 news articles, and 5 social media comments from online datasets as initial texts. To ensure that those initial texts covered the range of text properties we were interested in, we proceeded as follows: for *difficulty*, we measured the maximal and minimal *difficulty* d_{min} and d_{max} of texts from the scientific abstracts datasets, defined a linear space of 5 values $(d_i)_{i=1:5}$ between d_{min} and d_{max} and sampled 5 texts, each having a value of difficulty close to $(d_i)_{i=1:5}$. We then followed the same procedure for *toxicity*, using

* https://huggingface.co/datasets/CCRss/arxiv_papers_cs

† https://huggingface.co/datasets/RealTimeData/bbc_latest

‡ https://huggingface.co/datasets/FredZhang7/toxi-text-3M/blob/e0e5b168b4a7e14e84f07271bfe1c6b42bc91cc train-deduplicated.csv

the dataset of social media comments; for *positivity*, using the dataset of news articles; *length*, using the dataset of news articles.

Tasks To determine the effects of instructions on the evolution of content over generations of LLMs, we prompt each chain of LLMs with three different tasks encompassing typical uses of LLMs:

Rephrase: LLMs are instructed to paraphrase the received text without modifying its meaning. This task is relevant for applications such as text simplification, or for content summarization.

Take inspiration: agents are instructed to take inspiration from the received text to produce a new one. It can be used in creative writing, where the goal is to generate new and original content.

Continue: agents are instructed to continue the received text. It is relevant for applications such as dialogue generation, in order to generate coherent and relevant responses to user inputs, or for content generation in storytelling and gaming.

Tasks remained consistent within each chain. The exact prompt used for each task is reported in Appendix Section 21.

Models To assess whether and how cultural evolution dynamics are affected by the model specifications, we run identical experiments using six different models, all commonly used, from three different companies and with varying sizes: GPT-4o-mini, GPT-3.5-turbo-0125 (referred to as ”GPT3.5”) , Llama3-8B-Instruct (”Llama3-8B”), Mistral-7B-Instruct-v0.2 (”Mistral-7B”), Llama3-70B-Instruct (”Llama3-70B”), Mixtral-8x7B-Instruct-v0.1 (”Mixtral-8x7B”). For inference, we used the OpenAI API [§] to run GPT-4o-mini and GPT3.5 and the HuggingFace’s Transformer library (Wolf et al. 2019) for other models.

Pre-processing outputs Data analyses revealed that, on the *Continue* task, when using Mistral-7B, agents of the chains would sometimes start outputting very long text by filling them with “#*some_keyword*”. As this behavior created a few outliers, we thought it would be better to filter-out those “#*some_keyword*” when performing the main analyses. This behavior is nevertheless an interesting result, reminiscent of the collapsing dynamics found when training LLMs on their own output (Shumailov et al. 2023). We therefore discuss it separately in Appendix E.2.

Hyperparameters We use the following hyperparameters for generations in all models. Temperature was set to 0.8 with and top_p to 0.95. All models, except GPT3.5, bfloat16 precision was used.

Prompts used In our experiments, each task was induced by a specific instruction (prompt), which is given to each agent in the chain. For the *Rephrase* task, the instruction is: “You will receive a text. Your task is to rephrase this text without modifying its meaning. Just output your new text, nothing else. Here is the text:”, for the *Inspiration* task, the instruction is: “You will receive a text. Your task is to create a new original text by

[§] https://openai.com/index/openai-api/

taking inspiration from this text. Just output your new text, nothing else. Here is the text:", and for the *Continue* task, the instruction is: "You will receive a text. Your task is to continue this text. Just output your new text, nothing else. Here is the text:".

Examples of stories Here we provide examples of stories that were given as input and stories that were generated in the last iteration of some chains. Table E.1 shows one example for each task. Complete data can be found on the companion website [¶] using the Data Explorer tool.

E.1.2 Metrics

Iterated transmissions may affect the generated text in several ways. We focus on four, orthogonal properties for each text which could be automatically measured. *Toxicity*, *Positivity* and *Length* are computed as in the previous chapter (as described in D.2.3), and *Difficulty*:

- *Toxicity*. We assess the level of toxicity in generated texts using the Detoxify library, a classifier developed for the Jigsaw Toxic Comment Classification Challenges (see `https://github.com/unitaryai/detoxify/tree/master`. This classifier defines toxicity as the presence of rude, disrespectful, or unreasonable language in a text and assigns a probability score ranging from 0.0 (benign and non-toxic) to 1.0 (highly likely to be toxic). Trained on a large dataset of human-labeled comments from various online platforms, the classifier use a transformer-based architecture to analyze the text's context and meaning, identifying patterns indicative of toxicity.
- *Positivity*. We employ the `SentimentIntensityAnalyzer` tool from the NLTK library to assess the positivity of generated texts. The tool is based on the Valence Aware Dictionary and sEntiment Reasoner (VADER) method (Hutto and Gilbert 2014), which is a lexicon and rule-based sentiment analysis tool specifically designed for social media data. It uses a combination of lexical features, such as words and their semantic orientation, to determine the overall sentiment of a text. In the VADER method, every word in the vocabulary is rated with respect to its positive or negative sentiment and the intensity of that sentiment. The `SentimentIntensityAnalyzer` uses this information to calculate a sentiment score for the text, ranging from -1.0 (highly negative) to 1.0 (highly positive).
- *Difficulty*. We estimate the difficulty of generated texts using the Gunning-Fog index. In the method, complex words are defined as those with three or more syllables, excluding proper nouns, familiar jargon (and removing common suffixes as syllables). We used textstat to compute it.

E.1.3 Attractor strength and position

Human cultural evolution shows that cultural traits sometimes evolve towards attractor states, i.e., content that invites convergence even with different starting points (Kalish, Griffiths, and Lewandowsky 2007; Miton,

[¶] https://sites.google.com/view/llms-play-telephone

Claidière, and Mercier 2015; Miton et al. 2020; Buskell 2017). Therefore, we were interested in whether transmission chains with LLMs would show similar attractor dynamics, and whether these depend on the model and task used in the chain. The concept of *cultural attractor* is not consistently formalized in the human cultural evolution literature (Buskell 2017). Here, we defined attractors as the theoretical equilibrium point to which the iterated generation process (defined in E.1.1) may eventually converge.

We mathematically define attractors in terms of two properties of interest: its position (i.e., the location in output generation space the process converges toward) and its strength (i.e., the intensity to which generated outputs are pulled toward it). This is visualized in Figure E.1 in the Appendix. The strength takes values in $[0, 1]$, which allows for a continuous notion of an attractor: rather than being a binary concept that either exists or does not, attractors here lie on a spectrum, covering systems without attraction effects (strength=0) to ideal attractors (strength=1).

To compute position and strength, we use the simulated data to fit a linear regression predicting the value of a property at the end of the chain (i.e. after $n_{generations}$ as a function of its value in the initial text). For example for a given text *property*, we fit:

$$property(n_{generations}) = I + s * property_{initial}$$

, where I is the estimated intercept and s the estimated slope. This enables us to estimate the final output of a new chain starting from the final output of the previous chain as:

$$property(2 * n_{generations}) = I + s * property(n_{generations}).$$

The fitted linear regression thus allows to define a recurrent relationship between the output of a chain as a function of the output of the previous chain:

$$property(k * n_{generations}) = I + s * property((k-1) * n_{generations}).$$

This relationship is a linear recurrence sequence which can be rewritten as:

$$property(k * n_{generations}) = s^k * (property_{initial} - l) + l, l\frac{I}{1-s}$$

, If $|s| < 1$, then the sequence converges, its limit is l and its convergence rate is $1-s$. We can therefore use the estimated relationship to determine if an attractor exists ($|s| < 1$) and, if so, estimate its position $l = \frac{I}{1-s}$ and strength $1-s$.

To validate that these theoretical fixed points correctly capture attraction dynamics, we estimated their positions using only data from the *first 10 generations* of each chain, and compared the predictions with the actual output after *50 generations*. Visual inspection of the results (Appendix E.2.7) confirmed that our method is suited for estimating the strength and position of attractors.

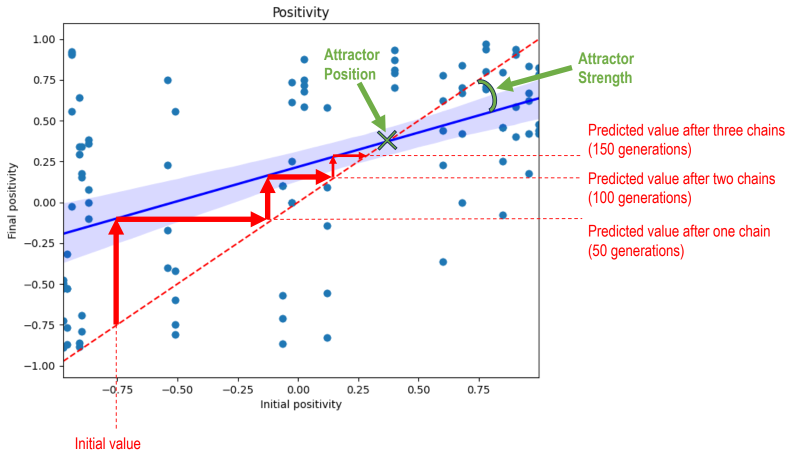


Figure E.1: Method for estimating attractor strength and position. This figures depicts the method introduced in Section E.1.3 to estimate the strength and position of theoretical attractors. Each dot in this figure corresponds to one chain, for a total of 100 chains (20 initial texts * 5 seeds). The position of a dot on the x-axis corresponds to the value of the property (*positivity* in this example) in the initial text, while the position on the y-axis corresponds to the value of this property of the text produced after 50 generations. We then used these 100 data points to fit a linear regression predicting the relationship between the initial and final values of the property.

Table E.1: Examples of starting stories and the corresponding final stories for chains with GPT3.5 on the three tasks

Description	Story
Starting story	You are certainly no friend of mine. You have accused me of lying about what you had said, and run away when I proved by actual quotation that the accusation was false. We both know that, even though you praise humility, you are not humble enough to apologize. You sneered at my combat experience, saying “A lot of so called “combat veterans” of Vietnam smelled more perfume from call girls than they smelled cordite” and “So when you were an Army officer in Vietnam (even though you spent your time inside of Danang airbase, with at least two battalions of infantry marines on the wire) what was the combat load for M-16 ammo per soldier on a daily patrol?” An actual friend would not have written such things. No, you are no friend of mine, you ignorant, arrogant, hypocritical blow-hard. You should be able to guess that I do not feel friendly towards you
Final story (Continue)	Your laughter and light will always be a beacon of hope in our darkest days. Your presence may be gone, but your spirit will forever be alive in our hearts. We will carry on your legacy of kindness and love, spreading your positivity to all those we encounter. Your memory will never fade, as we hold you close in our thoughts and actions. Rest easy, knowing that you are surrounded by our love and gratitude. You may be gone, but you will never be forgotten. Until we meet again, dear friend, know that you are always with us.
Final story (Inspiration)	A midst the chaos of our busy lives, it is essential to pause and prioritize forming genuine connections with those around us. By being fully present and showing empathy, we can cultivate relationships that are deep and fulfilling. Authenticity is the key to creating bonds that bring true joy and contentment into our lives. Engaging in open and sincere dialogues, sharing our vulnerabilities, and striving to forge meaningful connections are all essential in nurturing authentic relationships. Let’s come together to create a community where empathy and mutual respect are the guiding principles, and where every interaction is infused with love and gratitude. These authentic connections serve as a support system rooted in compassion and generosity, uplifting and inspiring each other as we navigate the ups and downs of life. Together, we can weave a network of relationships that exude positivity and light, enriching our lives in meaningful and transformative ways.
Final story (Rephrase)	I need to end our friendship since you won’t apologize for accusing me of dishonesty, ignoring evidence, and making disrespectful comments about my time in Vietnam. Your behavior shows a lack of empathy, arrogance, and insincerity, qualities that are not in line with those of a true friend.

E.2 Additional experiments

E.2.1 To what extent do multi-turn transmissions affect the evolution of properties?

One of our questions is how content evolves over multi-turn transmissions compared to single-turn settings. To address this point, we compare the distribution of a given property in the generated texts at the first generation to the distributions at subsequent generations. Thus for each model and task, we look at the properties of each of the 100 generated texts (20 transmissions chains * 5 seeds) at each generation, which gives us a sample of 100 property values for each value. Using a Kolmogorov–Smirnov test (Massey 1951), we then test whether the sample obtain at each generation comes from the same distribution as the sample obtained after the first generation. If we can confidently reject the hypothesis that the sample of property values at the end of the transmission chain comes from the same distribution as the sample obtained after the first generation, this would confirm that looking at outputs after a single-turn transmission is not enough for predicting output properties in a multi-turn setting.

Qualitative analyses from section Section 6.2.1 appear to suggest that multi-turn transmissions lead texts to acquire different properties compared to single-turn settings. To quantitatively evaluate this observation, we use Kolmogorov–Smirnov (KS) tests (Massey 1951) to estimate the compare property distributions after a single interaction and after multiple interactions. In Figure E.2, we report for each model, task and property the p-value of the KS test for the null hypothesis H_0: *"The text properties at generation i are sampled from the same distribution as the text properties after generation 1"*. Across most instances, we observe that the p-values steadily decrease, indicating that observing the given distribution under the null hypothesis becomes less and less likely with generations. We observe that this is more often the case for less constrained tasks (*Take Inspiration* and *Continue*, second and third columns) than for more constrained task (*Rephrase*, first column). This finding confirms that studying single-turn interactions is in general not sufficient for analyzing the properties of interacting LLMs' outputs. This warrants a more detailed account of the cultural dynamics across iterated interactions among LLMs.

E.2.2 Effect of temperature

Increasing the temperature appears to lead to stronger attractors only in constrained tasks (*Rephrase* and *Take inspiration*), but not in the more open- ended task *Continue* (Figure E.3a). One interpretation might be that increasing temperature relaxes constraints on the content that can be produced, thus leading to stronger attractors. This effect would therefore be more significant for tasks that are quite constrained.

E.2.3 Effect of fine-tuning

We observe that fine-tuning can shift the attractors' positions (Figure E.3b): the attractor for *length* is lower, and the attractor for *difficulty* higher, for

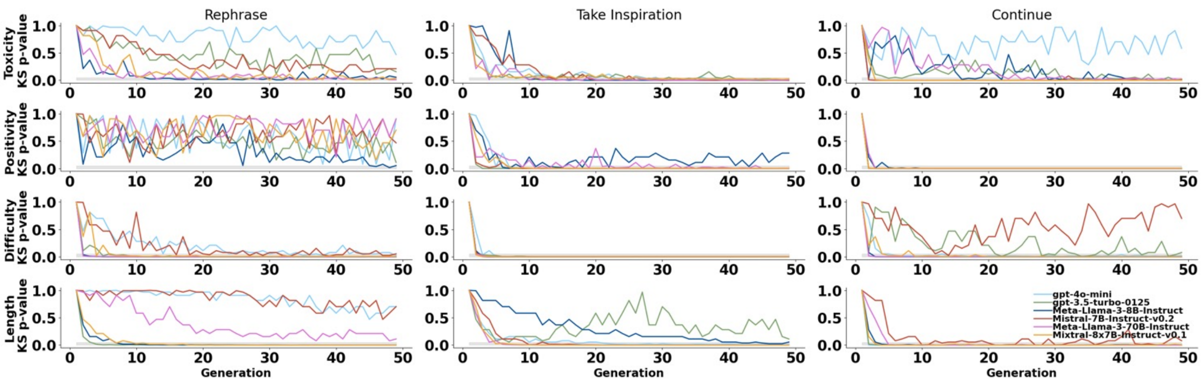


Figure E.2: Text properties are affected by transmissions beyond the first one. p-values of the KS-test for the null hypothesis H_0: *"The text properties at generation i are sampled from the same distribution as the text properties after generation 1"*, for each task (columns), property (rows) and models (colors). The gray shaded area represents p-values lower than 0.05. Over most instances, p-values decrease over generation and become close to 0, indicating that multi-turn transmissions lead to significantly different distributions compared to single-turn interactions.

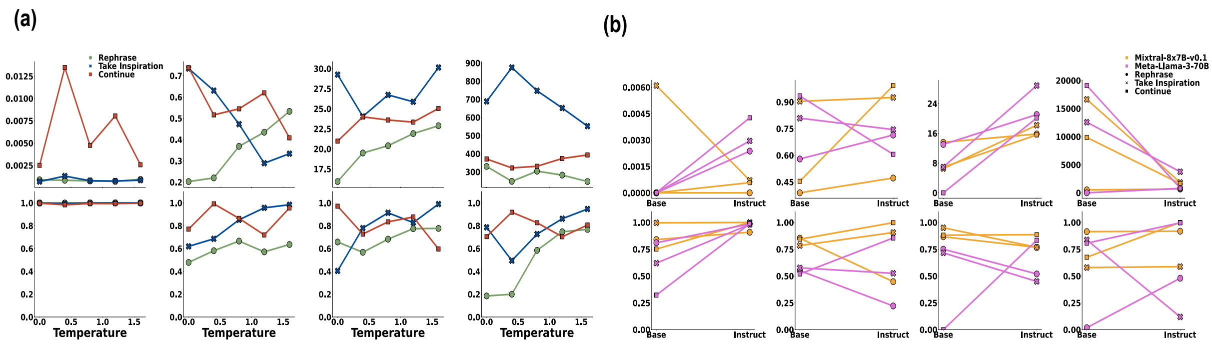


Figure E.3: Effect of temperature (a) and fine-tuning (b) on attractors. (a) Attractor positions (top row) and strength (bottom row) for different values on temperature (x-axis), for model *Llama3-8B-Instruct*. The main visible effect is that increasing temperature increases attraction strength for tasks *Rephrase* and *Take Inspiration*, but not for *Continue*. **(b)** Attractor positions (top row) and strength (bottom row) for *Base* and *Instruct* versions of *Mixtral-8x7B* and *Llama3-70B*. Fine-tuning appears to increase the strength of attraction for *toxicity*, increases the position of the attractor for *difficulty*, and decreases the position of the attractor for *length*.

Instruct models compared to Base models. For *toxicity* and *positivity*, we do not observe very significant shifts. This may indicate that Base models were already quite aligned with human preferences in terms of *toxicity* and *positivity* even before fine-tuning, possibly due to techniques such as data curation. *Length* and *difficulty* may have been less targeted by such techniques, and fine-tuning may therefore have shifted the attractors' positions towards human preferences. As for the strength of attractors, we observe that fine-tuning seems to increase attraction strength for *toxicity*, but to reduce it for *difficulty*. This may suggest that for properties on which humans have strong, uniform preferences (such as *toxicity*), fine-tuning leads to stronger attractors, while for properties on which humans have weaker and more heterogeneous preferences, it mitigates the strength of attractors that came from the training data. This analysis provides insight about how attractors are formed, and reveals that both the choice of training data and fine-tuning processes may impact LLMs in ways that only become significant in the case of multi-turn behaviors.

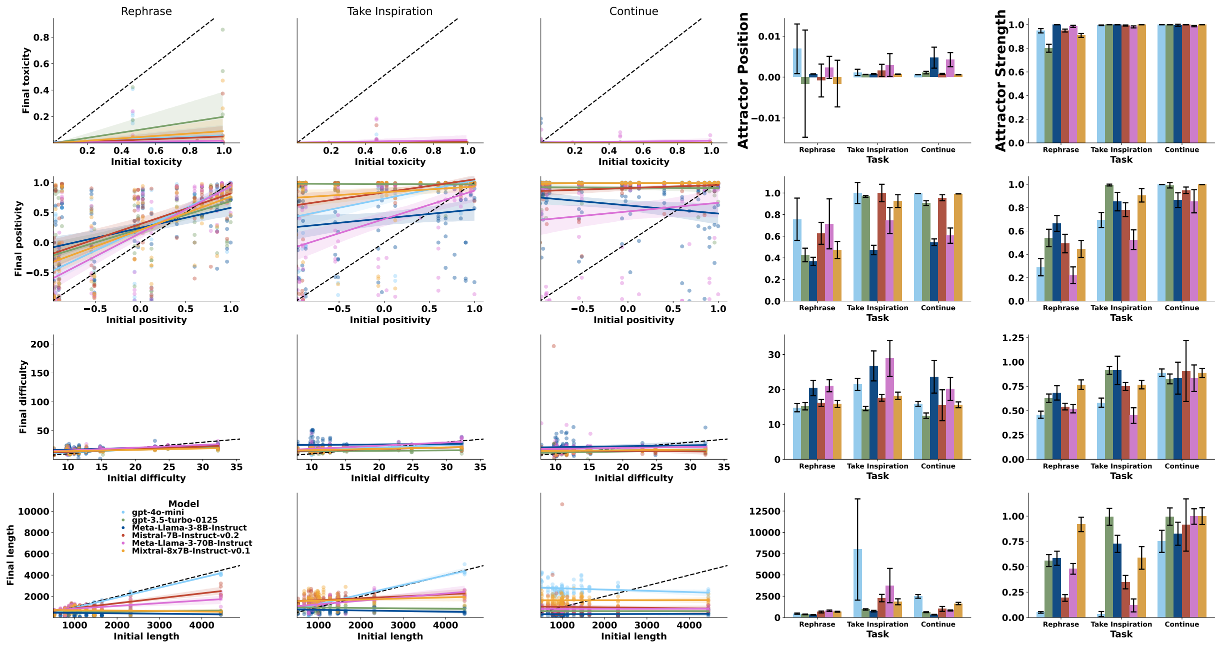


Figure E.4: Fitted linear regressions used to compute attractors strength and position. For three tasks (Rephrase, Take Inspiration, Continue), five models, and three metrics (*toxicity*, *positivity*, *difficulty*, *length*), we plot (Mean ± SE) the relationship between the metric value of the initial human-written text (input to the first agent) and the value of the final LLM-generated text (output of the last agent). A slope close to zero indicates strong attraction, while the value at the intersection with the diagonal captures the position of the attractor.

E.2.4 Robustness check and controls

Increasing the size of the set of initial texts

To verify that the results presented in the main text hold when using a larger set of initial texts, we ran additional experiments with Meta-Llama-3-8b using 100 different initial texts, using the same sampling procedure as for the main experiment (see Section E.1). We observe that the trends remain the same with 100 initial texts as with 20 initial texts, and that the standard deviation intervals for 100 initial texts include – or are very close to including – the values estimated with 20 initial texts (with only one exception out of 24 values (Figure E.5)

Different phrasing of the instructions prompts

To verify that the results presented in the main text hold when using different phrasings of the initial prompts, we ran additional experiments with *Llama-3-8B* using 5 different phrasings of instructions prompts for each of the three. Those exact prompts are as follows:

Rephrase

- "You will be given a text. Your job is to reword this text without changing its meaning. Only provide your revised text, nothing else. Here is the text:"
- "A text will be provided to you. Your task is to rephrase it, keeping its meaning intact. Only output the rephrased text, and nothing additional. Here is the text:"

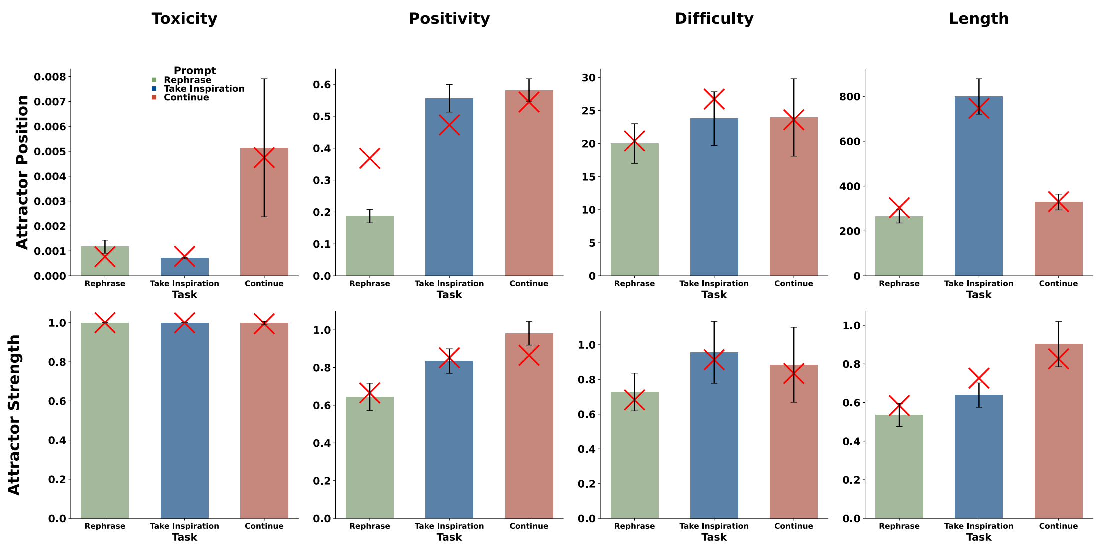


Figure E.5: Attractor strengths and positions over 100 initial texts. Attractor position (first row) and strength (second row) for four text properties (column) and three tasks (colors). The height of the bars are the position and strength of the attractors for a set of 100 initial texts. The red crosses indicate the values estimated in the main experiment using a set of 20 initial texts (Section 6.2.2). This reveals that our results are robust to increasing the sample size of the initial texts dataset.

- "You'll receive a text, and your job is to rephrase it without altering its meaning. Just output your new version, nothing more. Here is the text:"
- "A text will be sent to you. Your role is to rephrase it while keeping the meaning the same. Only display your new text, with nothing extra. Here is the text:"
- "You will be provided with a text. Your task is to reword it without changing the intended meaning. Output just your rephrased text, nothing else. Here is the text:"

Inspiration

- "You'll be given a text, and your task is to craft a new, original text inspired by it. Only provide your new version, with nothing additional. Here is the text:"
- "A text will be provided to you. Your task is to create an original text based on this inspiration. Just output your new version, nothing extra. Here is the text:"
- "You will receive a text. Your job is to generate an original text inspired by it. Only show your new version, without adding anything else. Here is the text:"
- "You'll receive a text, and your task is to create a new text inspired by it. Simply display your new version, with no additional output. Here is the text:"
- "You will be sent a text. Your role is to produce an original text inspired by it. Only present your new text, nothing more. Here is the text:"

Continue

- "You'll be provided with a text. Your job is to extend this text. Only output your continuation, nothing additional. Here is the text:"

- "A text will be given to you. Your task is to carry on from this text. Just display your new continuation, with nothing extra. Here is the text:"
- "You'll receive a text. Your role is to continue from where this text ends. Only present your extension, with no additional output. Here is the text:"
- "A text will be sent to you, and your job is to complete it by continuing from its end. Only output your continuation, nothing more. Here is the text:"
- "You will get a text. Your task is to extend it further. Just display your continuation, without adding anything else. Here is the text:"

This revealed that our results are robust to different paraphrasing of the same prompt: indeed, the interval of the standard deviations over the 5 paraphrased prompts always contains – or almost contains – the values estimated with the original prompt in the main experiment. (Figure E.6)

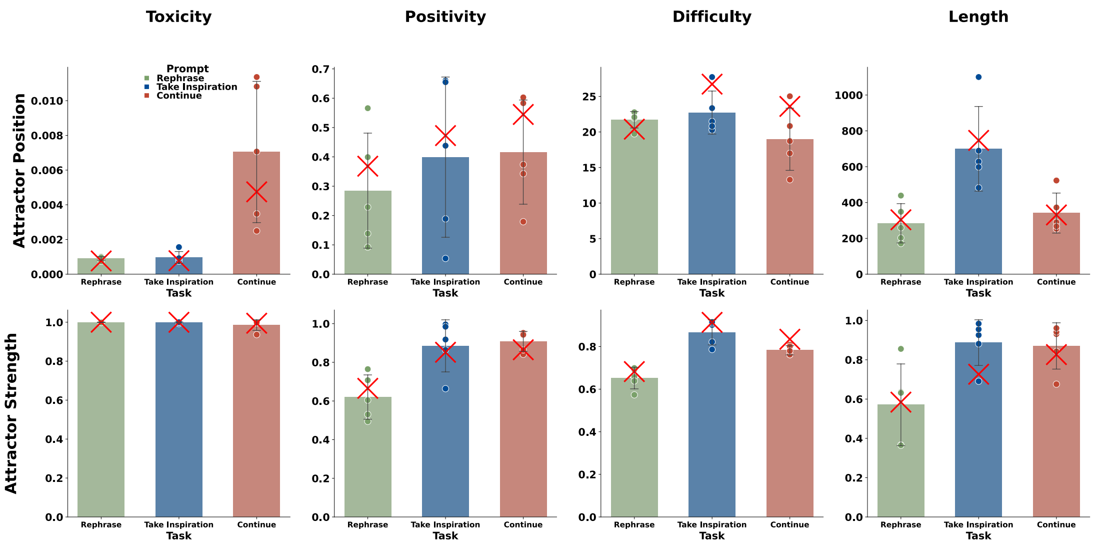


Figure E.6: Attractor strengths and positions for different phrasings of the instruction prompts. Attractor position (first row) and strength (second row) for four text properties (column) and three tasks (colors). The height of the bars represent the average position and strength of the attractors over the five different phrasings. Individual dots correspond to each different phrasing. The red crosses indicate the values estimated in the main experiment using a set of 20 initial texts (Section 6.2.2). This reveals that our results are robust to increasing the sample size of the initial texts dataset.

Effect of less versus more constrained tasks on attractors

In the results from the main experiments, we observed that less constrained tasks (such as *Continue*) lead to stronger attractors than more constrained tasks (such as *Rephrase*). However, these two tasks vary on other dimensions than only the room for variation allowed. To verify our hypothesis, we conducted additional experiments with *Llama-3-8B* where we instructed the LLM to create a new text by making either “very minor”, “a few small”, “moderate”, “notable” or “radical” changes to the received text.

The exact prompts were as follows:

- "You will receive a text. Your task is to create a new original text by taking inspiration from this text, making only very minor changes. Just output your new text, nothing else. Here is the text:"
- "You will receive a text. Your task is to create a new original text by taking inspiration from this text, making a few small changes. Just output your new text, nothing else. Here is the text:"
- "You will receive a text. Your task is to create a new original text by taking inspiration from this text, making moderate changes. Just output your new text, nothing else. Here is the text:"
- "You will receive a text. Your task is to create a new original text by taking inspiration from this text, making notable changes. Just output your new text, nothing else. Here is the text:"
- "You will receive a text. Your task is to create a new original text by taking inspiration from this text, making radical changes. Just output your new text, nothing else. Here is the text:"

This experiment confirmed our initial interpretation, as less constrained tasks indeed exhibit stronger attractors (FigureE.7). The only exception is Length. We interpret this by the fact that going from “very minor” to “radical” changes mainly refers to the semantic of the text. As a consequence, the instructions to make “minor changes” is not more constrained than to make “radical changes” with respect to Length.

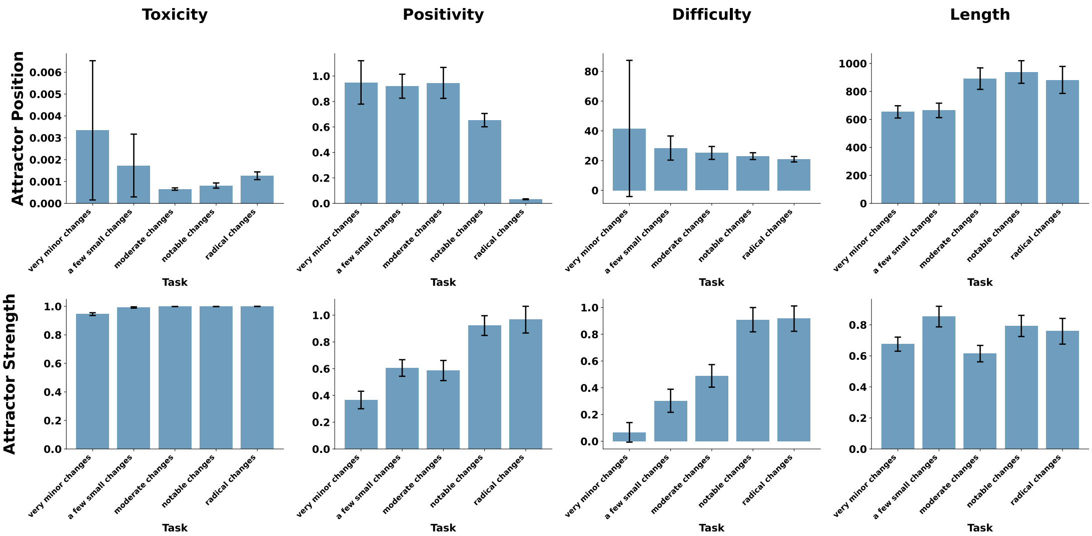


Figure E.7: Effect of less versus more constrained tasks on attractors. Attractor position (first row) and strength (second row) for four text properties (column) as a function of the room for variation allowed in the instruction. These results confirm our hypothesis that less constrained tasks lead to stronger attractors. The only exception is Length. We interpret this by the fact that going from "very minor" to "radical" changes mainly refers to the semantic of the text. As a consequence, the instructions to make "minor changes" is not more constrained than to make "radical changes" with respect to Length.

Effect of heterogeneous transmission chains

As the study of LLMs' multi-turn dynamics remains unexplored, it appeared necessary to start with a setting where causal variables can be isolated, so as to lay the foundation for incrementally improving our understanding of LLMs cultural dynamics. As a consequence, the main experiments focused on homogeneous chains where the multi-turn dynamics of different models can be assessed in isolation. However, we also investigate the effect of having heterogeneous chains, where two different models interact (Figure E.8). We compared 4 conditions: homogeneous chains of Mistral-7B models, homogeneous chains of Llama-3-8B models, heterogeneous chains of Mistral-7B and Llama-3-8B models starting with Mistral-7B and heterogeneous chains of Mistral-7B and Llama-8B models starting with Llama-3-8B. We found that although the position of the attractor in heterogeneous chains is often in between the position of the homogeneous chains' attractors, it is not systematically the case.

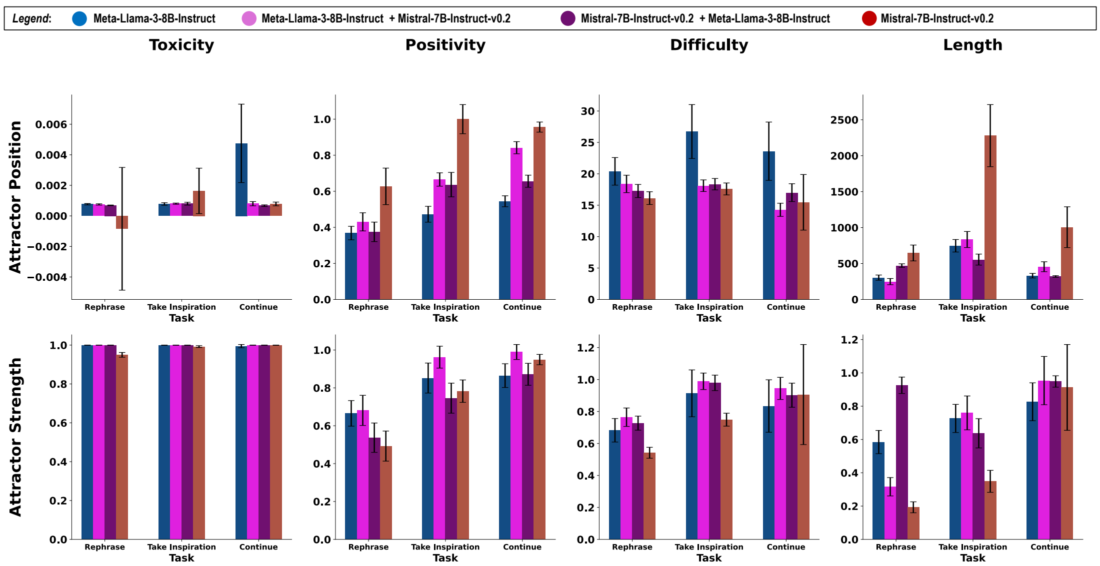


Figure E.8: Comparison of homogeneous and heterogeneous transmission chains. Attractor position (first row) and strength (second row) for four text properties (column) and three different tasks, for homogeneous chains of Llama-3-8B models (blue), homogeneous chains of Mistral-7B models (red), heterogeneous chains of Mistral-7B and Llama-3-8B models starting with Mistral-7B (dark purple) and heterogeneous chains of Mistral-7B and Llama-8B models starting with Llama-3-8B (light purple).

E.2.5 Statistical models

Kolmogorov-Smirnov tests

To quantitatively evaluate whether multi-turn transmission lead to significantly different outcomes than single-turn transmission, we use Kolmogorov–Smirnov (KS) tests (Massey 1951) to estimate the compare distributions of text properties after a single interaction and after multiple interactions. Although we calculate p-values repeatedly (once for each generation, model and task), in our cases applying corrections to control for the False Discovery Rate (FDR) was in our case not necessary. Indeed, controlling for the FDR using methods such as Bonferroni correction is necessary in cases where many statistical tests are conducted, as it increases the likelihood that at least one of them is found significant "by chance" (Family-Wise Error Rate; Colas, 2022). With respect to our set-up, this would have been necessary if we concluded that multi-turn interactions lead to significant differences when at least one of the 49 p-values (one by generation) was below the significance threshold. However, we rather report all p-values, and draw conclusions from the trend observed over all generations, rather than from single p-values. Therefore, if we observe a general trend of decreasing p-values, we can conclude that observing the given distribution under the null hypothesis becomes less and less likely with generations. FDR corrections are thus unnecessary for drawing this conclusion.

Bayesian models

We performed statistical analyses using the Python package *pymc* (Wiecki et al. 2024) to fit Bayesian models.

- **Model 1** We fitted a model predicting the attractor strength (Figure 6.3) as a function of the Task, Model and Property: $Strength \sim \mathcal{N}(\mu, \sigma^2)$
  where $\mu = \alpha_{Task} + \beta_{Model} + \gamma_{Property}$
  Priors for parameters a, b and c were standard normal distribution, and standard half-normal distribution for σ.
- **Model 2** For each Property, we fitted a model predicting the attractor position (Figure 6.3) as a function of the Task and Model: $Position_{property} \sim \mathcal{N}(\mu, \sigma^2)$
  where $\mu = \alpha_{Task} + \beta_{Model}$

To determine the significance of the difference between estimated parameters, we computed the 95% credibility intervals of the difference by sampling from the posteriors. In Tables E.4 to E.12, we provide those credibility intervals. Intervals that do not contain 0 signal statistically significant differences.

	rephrase	inspiration	continue	
rephrase	[0.0000 ; 0.0000]	[-0.2372 ; -0.0353]	[-0.4187 ; -0.2195]	
inspiration	[0.0353 ; 0.2372]	[0.0000 ; 0.0000]	[-0.2824 ; -0.0840]	
continue	[0.2195 ; 0.4187]	[0.0840 ; 0.2824]	[0.0000 ; 0.0000]	

Table E.2: 95% Credible Intervals for posterior differences between prompts for attractor strength

Table E.3: 95% Credible Intervals for posterior differences between model for attractor strength

	gpt-4o-mini	gpt-3.5-turbo-0125	Meta-Llama-3-8B-Instruct	Mistral-7B-Instruct-v0.2	Meta-Llama-3-70B-Instruct	Mixtral-8x7B-Instruct-v0.1
gpt-4o-mini	[0.0000 ; 0.0000]	[-0.3539 ; -0.0699]	[-0.3289 ; -0.0451]	[-0.2361 ; 0.0487]	[-0.1644 ; 0.1208]	[-0.3501 ; -0.0649]
gpt-3.5-turbo-0125	[0.0699 ; 0.3539]	[0.0000 ; 0.0000]	[-0.1161 ; 0.1673]	[-0.0228 ; 0.2603]	[0.0490 ; 0.3346]	[-0.1385 ; 0.1478]
Meta-Llama-3-8B-Instruct	[0.0451 ; 0.3289]	[-0.1673 ; 0.1161]	[0.0000 ; 0.0000]	[-0.0500 ; 0.2351]	[0.0256 ; 0.3087]	[-0.1617 ; 0.1209]
Mistral-7B-Instruct-v0.2	[-0.0487 ; 0.2361]	[-0.2603 ; 0.0228]	[-0.2351 ; 0.0500]	[0.0000 ; 0.0000]	[-0.0686 ; 0.2134]	[-0.2561 ; 0.0277]
Meta-Llama-3-70B-Instruct	[-0.1208 ; 0.1644]	[-0.3346 ; -0.0490]	[-0.3087 ; -0.0256]	[-0.2134 ; 0.0686]	[0.0000 ; 0.0000]	[-0.3282 ; -0.0430]
Mixtral-8x7B-Instruct-v0.1	[0.0649 ; 0.3501]	[-0.1478 ; 0.1385]	[-0.1209 ; 0.1617]	[-0.0277 ; 0.2561]	[0.0430 ; 0.3282]	[0.0000 ; 0.0000]

Table E.4: 95% Credible Intervals for posterior differences between measures for attractor strength

	toxicity	positivity	difficulty	length
toxicity	[0.0000 ; 0.0000]	[0.1345 ; 0.3626]	[0.1274 ; 0.3584]	[0.2422 ; 0.4747]
positivity	[-0.3626 ; -0.1345]	[0.0000 ; 0.0000]	[-0.1201 ; 0.1094]	[-0.0054 ; 0.2273]
difficulty	[-0.3584 ; -0.1274]	[-0.1094 ; 0.1201]	[0.0000 ; 0.0000]	[-0.0014 ; 0.2330]
length	[-0.4747 ; -0.2422]	[-0.2273 ; 0.0054]	[-0.2330 ; 0.0014]	[0.0000 ; 0.0000]

Table E.5: 95% Credible Intervals for posterior differences between model for attractor position - toxicity

	gpt-4o-mini	gpt-3.5-turbo-0125	Meta-Llama-3-8B-Instruct	Mistral-7B-Instruct-v0.2	Meta-Llama-3-70B-Instruct	Mixtral-8x7B-Instruct-v0.1
gpt-4o-mini	[0.0000 ; 0.0000]	[-0.0012 ; 0.0069]	[-0.0033 ; 0.0049]	[-0.0016 ; 0.0064]	[-0.0043 ; 0.0037]	[-0.0010 ; 0.0070]
gpt-3.5-turbo-0125	[-0.0069 ; 0.0012]	[0.0000 ; 0.0000]	[-0.0061 ; 0.0020]	[-0.0045 ; 0.0035]	[-0.0071 ; 0.0009]	[-0.0039 ; 0.0042]
Meta-Llama-3-8B-Instruct	[-0.0049 ; 0.0033]	[-0.0020 ; 0.0061]	[0.0000 ; 0.0000]	[-0.0024 ; 0.0056]	[-0.0051 ; 0.0030]	[-0.0019 ; 0.0063]
Mistral-7B-Instruct-v0.2	[-0.0064 ; 0.0016]	[-0.0035 ; 0.0045]	[-0.0056 ; 0.0024]	[0.0000 ; 0.0000]	[-0.0066 ; 0.0014]	[-0.0034 ; 0.0046]
Meta-Llama-3-70B-Instruct	[-0.0037 ; 0.0043]	[-0.0009 ; 0.0071]	[-0.0030 ; 0.0051]	[-0.0014 ; 0.0066]	[0.0000 ; 0.0000]	[-0.0007 ; 0.0073]
Mixtral-8x7B-Instruct-v0.1	[-0.0070 ; 0.0010]	[-0.0042 ; 0.0039]	[-0.0063 ; 0.0019]	[-0.0046 ; 0.0034]	[-0.0073 ; 0.0007]	[0.0000 ; 0.0000]

Table E.6: 95% Credible Intervals for posterior differences between prompt for attractor position - toxicity

	rephrase	inspiration	continue
rephrase	[0.0000 ; 0.0000]	[-0.0031 ; 0.0000]	[-0.0040 ; -0.0009]
inspiration	[-0.0000 ; 0.0031]	[0.0000 ; 0.0000]	[-0.0025 ; 0.0006]
continue	[0.0009 ; 0.0040]	[-0.0006 ; 0.0025]	[0.0000 ; 0.0000]

Table E.7: 95% Credible Intervals for posterior differences between model for attractor position - positivity

	gpt-4o-mini	gpt-3.5-turbo-0125	Meta-Llama-3-8B-Instruct	Mistral-7B-Instruct-v0.2	Meta-Llama-3-70B-Instruct	Mixtral-8x7B-Instruct-v0.1
gpt-4o-mini	[0.0000 ; 0.0000]	[-0.0982 ; 0.3959]	[0.2023 ; 0.6959]	[-0.1887 ; 0.3048]	[-0.0172 ; 0.4735]	[-0.1299 ; 0.3673]
gpt-3.5-turbo-0125	[-0.3959 ; 0.0982]	[0.0000 ; 0.0000]	[0.0521 ; 0.5498]	[-0.3395 ; 0.1533]	[-0.1712 ; 0.3262]	[-0.2771 ; 0.2166]
Meta-Llama-3-8B-Instruct	[-0.6959 ; -0.2023]	[-0.5498 ; -0.0521]	[0.0000 ; 0.0000]	[-0.6410 ; -0.1471]	[-0.4723 ; 0.0229]	[-0.5813 ; -0.0818]
Mistral-7B-Instruct-v0.2	[-0.3048 ; 0.1887]	[-0.1533 ; 0.3395]	[0.1471 ; 0.6410]	[0.0000 ; 0.0000]	[-0.0767 ; 0.4176]	[-0.1860 ; 0.3139]
Meta-Llama-3-70B-Instruct	[-0.4735 ; 0.0172]	[-0.3262 ; 0.1712]	[-0.0229 ; 0.4723]	[-0.4176 ; 0.0767]	[0.0000 ; 0.0000]	[-0.3566 ; 0.1401]
Mixtral-8x7B-Instruct-v0.1	[-0.3673 ; 0.1299]	[-0.2166 ; 0.2771]	[0.0818 ; 0.5813]	[-0.3139 ; 0.1860]	[-0.1401 ; 0.3566]	[0.0000 ; 0.0000]

Table E.8: 95% Credible Intervals for posterior differences between prompt for attractor position - positivity

	rephrase	inspiration	continue
rephrase	[0.0000 ; 0.0000]	[-0.4662 ; -0.1133]	[-0.4465 ; -0.0938]
inspiration	[0.1133 ; 0.4662]	[0.0000 ; 0.0000]	[-0.1570 ; 0.1913]
continue	[0.0938 ; 0.4465]	[-0.1913 ; 0.1570]	[0.0000 ; 0.0000]

Table E.9: 95% Credible Intervals for posterior differences between model for attractor position - difficulty

	gpt-4o-mini	gpt-3.5-turbo-0125	Meta-Llama-3-8B-Instruct	Mistral-7B-Instruct-v0.2	Meta-Llama-3-70B-Instruct	Mixtral-8x7B-Instruct-v0.1
gpt-4o-mini	[0.0000 ; 0.0000]	[-2.6049 ; 2.8520]	[-2.9991 ; 2.4390]	[-2.6157 ; 2.7268]	[-2.9831 ; 2.4137]	[-2.6832 ; 2.7637]
gpt-3.5-turbo-0125	[-2.8520 ; 2.6049]	[0.0000 ; 0.0000]	[-3.1499 ; 2.2758]	[-2.7682 ; 2.6207]	[-3.1053 ; 2.2984]	[-2.8099 ; 2.6017]
Meta-Llama-3-8B-Instruct	[-2.4390 ; 2.9991]	[-2.2758 ; 3.1499]	[0.0000 ; 0.0000]	[-2.3698 ; 3.0545]	[-2.7175 ; 2.7392]	[-2.4107 ; 3.0411]
Mistral-7B-Instruct-v0.2	[-2.7268 ; 2.6157]	[-2.6207 ; 2.7682]	[-3.0545 ; 2.3698]	[0.0000 ; 0.0000]	[-3.0124 ; 2.3806]	[-2.6899 ; 2.6762]
Meta-Llama-3-70B-Instruct	[-2.4137 ; 2.9831]	[-2.2984 ; 3.1053]	[-2.7392 ; 2.7175]	[-2.3806 ; 3.0124]	[0.0000 ; 0.0000]	[-2.3859 ; 3.0178]
Mixtral-8x7B-Instruct-v0.1	[-2.7637 ; 2.6832]	[-2.6017 ; 2.8099]	[-3.0411 ; 2.4107]	[-2.6762 ; 2.6899]	[-3.0178 ; 2.3859]	[0.0000 ; 0.0000]

Table E.10: 95% Credible Intervals for posterior differences between prompt for attractor position - difficulty

	rephrase	inspiration	continue
rephrase	[0.0000 ; 0.0000]	[-3.0072 ; 2.2777]	[-2.6556 ; 2.6528]
inspiration	[-2.2777 ; 3.0072]	[0.0000 ; 0.0000]	[-2.2601 ; 2.9840]
continue	[-2.6528 ; 2.6556]	[-2.9840 ; 2.2601]	[0.0000 ; 0.0000]

Table E.11: 95% Credible Intervals for posterior differences between model for attractor position - length

	gpt-4o-mini	gpt-3.5-turbo-0125	Meta-Llama-3-8B-Instruct	Mistral-7B-Instruct-v0.2	Meta-Llama-3-70B-Instruct	Mixtral-8x7B-Instruct-v0.1
gpt-4o-mini	[0.0000 ; 0.0000]	[-1.8746 ; 3.6795]	[-1.8366 ; 3.7029]	[-2.1079 ; 3.4919]	[-2.2197 ; 3.3266]	[-2.0495 ; 3.4024]
gpt-3.5-turbo-0125	[-3.6795 ; 1.8746]	[0.0000 ; 0.0000]	[-2.7134 ; 2.8132]	[-2.9561 ; 2.5396]	[-3.1474 ; 2.4007]	[-2.9893 ; 2.5194]
Meta-Llama-3-8B-Instruct	[-3.7029 ; 1.8366]	[-2.8132 ; 2.7134]	[0.0000 ; 0.0000]	[-3.0299 ; 2.5205]	[-3.1786 ; 2.3807]	[-3.0437 ; 2.4675]
Mistral-7B-Instruct-v0.2	[-3.4919 ; 2.1079]	[-2.5396 ; 2.9561]	[-2.5205 ; 3.0299]	[0.0000 ; 0.0000]	[-2.9116 ; 2.6355]	[-2.7884 ; 2.7556]
Meta-Llama-3-70B-Instruct	[-3.3266 ; 2.2197]	[-2.4007 ; 3.1474]	[-2.3807 ; 3.1786]	[-2.6355 ; 2.9116]	[0.0000 ; 0.0000]	[-2.6617 ; 2.8778]
Mixtral-8x7B-Instruct-v0.1	[-3.4024 ; 2.0495]	[-2.5194 ; 2.9893]	[-2.4675 ; 3.0437]	[-2.7556 ; 2.7884]	[-2.8778 ; 2.6617]	[0.0000 ; 0.0000]

Table E.12: 95% Credible Intervals for posterior differences between prompt for attractor position - length

	rephrase	inspiration	continue
rephrase	[0.0000 ; 0.0000]	[-4.1791 ; 1.3268]	[-3.1691 ; 2.4195]
inspiration	[-1.3268 ; 4.1791]	[0.0000 ; 0.0000]	[-1.7409 ; 3.8265]
continue	[-2.4195 ; 3.1691]	[-3.8265 ; 1.7409]	[0.0000 ; 0.0000]

E.2.6 Discontinuities and collapsing behavior

In the main text, the experiment with the Mistral-7B model on the *Continue* task was analyzed by first filtering the hashtags, as discussed in Appendix E.1. Given, that this behavior is interesting in itself, we discuss it here in more details.

Figure E.9 shows the average length of text generated with the Mistral-7B model chain on the *Continue* task for five different seeds of the same story. We can observe several discontinuities in terms of the generated text length, i.e. at some iterations the length drastically increases or decreases. It is interesting to note that when the length decreases, it returns to the original value as before the first discontinuity. This suggests the existence of an attractor regarding this specific length. To better understand the cause of these discontinuities, Figure E.13 shows examples of stories generated before and after those discontinuities (for the seed number three in figure E.9). We can see that at generation 14 the model abruptly starts to generate many hashtags. It generates 283 hashtags, compared to 12 in the previous generation. At generation 45, we can see that the overall quality of the text decreased into generating solely hashtags and brief descriptions. This reduction in text quality is reminiscent of collapsing dynamics observed in iterative chains of LLMs, where each model was trained on the output of a previous one (Shumailov et al. 2023).

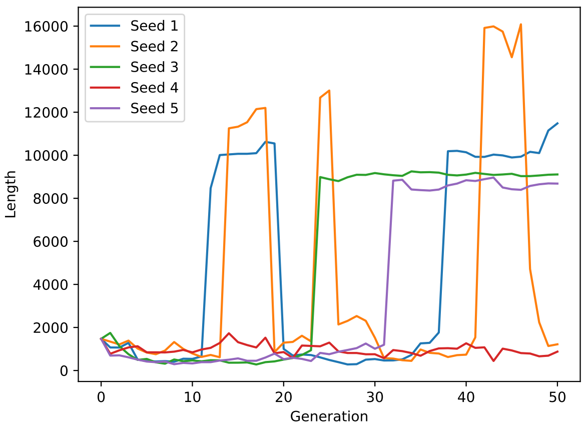


Figure E.9: Discontinuities and collapse in the Mistral-7B model chain. The lengths of generated stories are shown (without filtering out the hashtags) for five chains starting with the same initial story. We observe discontinuities, where the length drastically increases or decreases. After decreasing, the length of the story goes back to the original length, suggesting the existence of an attractor.

Table E.13: Examples of stories demonstrating the collapse and recovery in Mistral-7B chains on the *Continue* task for (seed 2 from figure E.9

Gen.	Story
13	We are thrilled about the progress we've made in making Xiangqi more accessible for all. Let's keep the conversation going and explore new ways to adapt the game for different abilities. Share your ideas, experiences, and success stories using the hashtags #CXAInclusiveXiangqi #XiangqiForAll #AccessibleXiangqi #XiangqiUnited #DisabilityInclusion #AdaptiveXiangqi #InclusiveGaming #AccessibleCommunity. Let's continue to learn from each other and create a vibrant, inclusive Xiangqi community that celebrates diversity and welcomes everyone. #UnitedWeGame #AccessibleXiangqiJourney #TogetherWeCan #XiangqiForEveryone
14	Let's exchange innovative ideas on modifying Xiangqi pieces, boards, and rules to accommodate various disabilities. #AdaptiveXiangqiDesigns #InclusiveXiangqiSolutions #TogetherWeAdapt #XiangqiEmpowerment #AccessibleXiangqiProgress #DisabilityFriendlyXiangqi #XiangqiInclusiveCommunity #BreakingBarriers #XiangqiForAllPlayers #AccessibleXiangqiChampions #Xiangqi-InclusionSuccessStories #XiangqiUnitedForAll #AccessibleXiangqiFuture #InclusiveXiangqiVision *(omitted 264 hashtags for clarity)* #XiangqiInclusiveGamingCommunityVision #XiangqiAccessibleGamingCommunityGrowth #XiangqiAccessibleGamingCommunityInnovation #XiangqiAccessibleGamingCommunityEmpowerment #XiangqiAccessibleGamingCommunityPassion
45	#DesignWithInclusiveDesignPhilosophyScaling: Embracing diversity and equality in design practices. #DesignWithUserCenteredDesignPhilosophyScaling: Putting users first in design decisions and experiences. #DesignWithInclusiveTechnologyPhilosophyScaling: Making technology accessible to all users, regardless of abilities. #DesignWithDigitalInclusionPhilosophyScaling: Ensuring everyone has equal access to digital resources and services. *(omitted 176 lines for clarity)*. #DesignWithUserTestingTrainingScaling: Scaling user testing training opportunities. #DesignWithAssistiveTechnologyTrainingScaling: Expanding assistive technology training opportunities. #DesignWithInclusive
49	#DesignWithGlobalAccessibilityInitiativesScaling: Expanding global accessibility initiatives and collaborations. *(omitted 7 lines for clarity)* #DesignWithInclusiveDesignTrendsScaling: Growing trends and innovations in inclusive design and accessibility. #DesignWithInclusiveDesignResourcesScaling: Expanding resources for inclusive design and accessibility knowledge and tools.

E.2.7 Validation of attractors position and strength estimation

The method introduced in Section E.1.3 gives the position and strength of a theoretical attractor (or theoretical fixed point). In order to validate our method, we verified that this theoretical prediction matches the actual data. To do so, we used the first 10 generations of each simulated chain to predict the strength and position of attractors for each task, model and property. We then compared this prediction with the actual properties of texts obtained after 50 generations. As shown in Figure E.10, transmission chains shifts the initial distribution of values in the direction of the predicted attractor. Moreover, the variance of the final distribution appears to reflect the predicted strength of the attractor. These results confirmed that the method we introduce is indeed suited for estimating the strength of position of attractors.

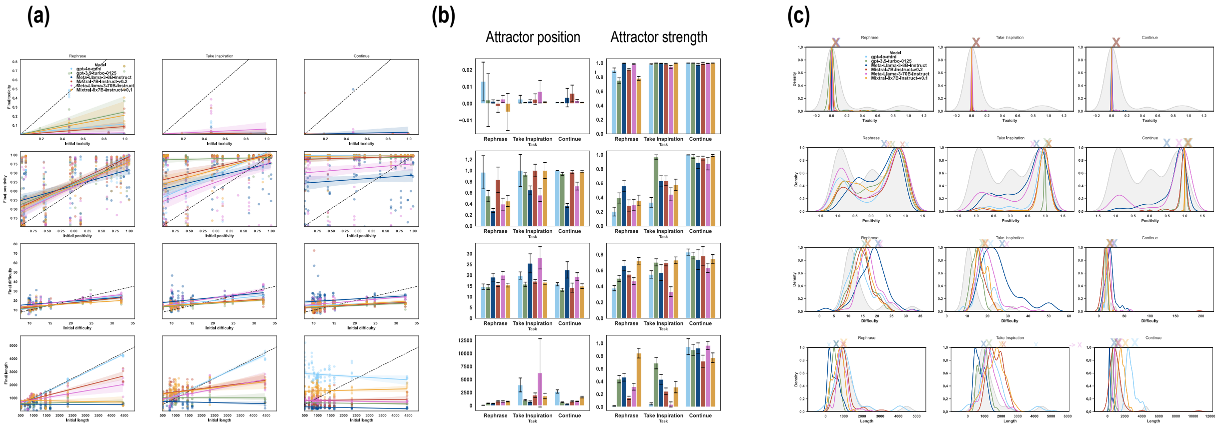


Figure E.10: Empirical validation of attractors position and strength estimation. To empirical verify that the method introduced in Section E.1.3 makes accurate prediction, we used the first 10 generations of each chain to fit the linear regression between initial and final property values **(a)**. We then used our method to estimate attractors' strength and position **(b)**. We then compared those predictions with the actual shifts in distribution observed after 50 generations **(c)**. The grey area represents the initial distribution of the corresponding property, and colored line show the distribution after 50 generations for each model. Crosses indicate the estimated position of theoretical attractors, and their size represent its strength. For the fourth row, second column, one attractor was outside the range of represented values and is thus represented with "-> X".

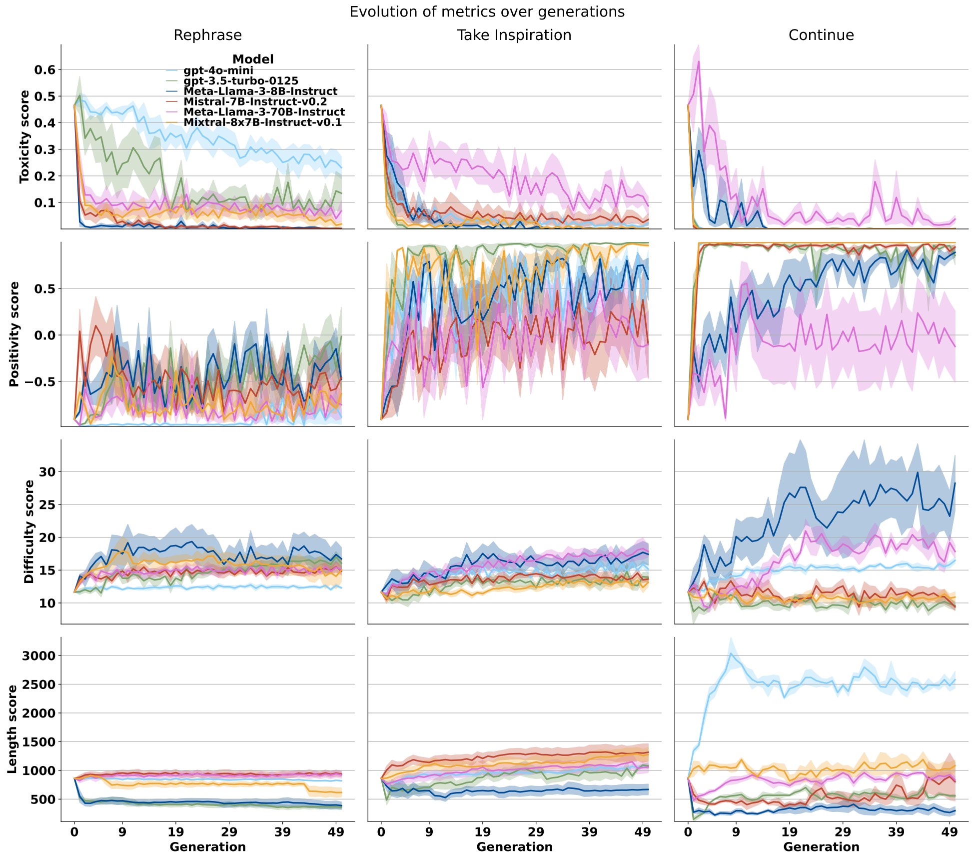


Figure E.11: Evolution of text properties starting with Initial Text 18 Single-step interactions are often not enough to predict multi-step interactions. For instance, regarding toxicity (for take inspiration) we see that at first Mistral appears less toxic at the first iteration, but after 9 generations Llama3-8B ends up being much less toxic. One may therefore choose Mistral-7B based on single-step evaluation, even though Llama3-8B is the optimal choice for many applications.

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Notation

The next list describes several symbols that will be later used within the body of the document.

c Speed of light in a vacuum inertial frame

h Planck constant

Greek Letters with Pronunciations

Character	Name	Character	Name
α	alpha *AL-fuh*	ν	nu *NEW*
β	beta *BAY-tuh*	ξ, Ξ	xi *KSIGH*
γ, Γ	gamma *GAM-muh*	o	omicron *OM-uh-CRON*
δ, Δ	delta *DEL-tuh*	π, Π	pi *PIE*
ϵ	epsilon *EP-suh-lon*	ρ	rho *ROW*
ζ	zeta *ZAY-tuh*	σ, Σ	sigma *SIG-muh*
η	eta *AY-tuh*	τ	tau *TOW (as in cow)*
θ, Θ	theta *THAY-tuh*	υ, Υ	upsilon *OOP-suh-LON*
ι	iota *eye-OH-tuh*	ϕ, Φ	phi *FEE, or FI (as in hi)*
κ	kappa *KAP-uh*	χ	chi *KI (as in hi)*
λ, Λ	lambda *LAM-duh*	ψ, Ψ	psi *SIGH, or PSIGH*
μ	mu *MEW*	ω, Ω	omega *oh-MAY-guh*

Capitals shown are the ones that differ from Roman capitals.