EU RIA H2020 Proposal Template

ROBHOOT

**Abstract**

Eco-evolutionary biology teaches us how interactions and traits evolve and diversify across levels of biological organization, from neurons to populations. Evolving networks in nature with ever chang-ing traits and connectivity patterns can inspire a new computing discovery for a global-sustainable knowledge-inspired society. Many studies have shown global sustainability could be achieved by strengthening transparency, communication, and rapid access to discovery technologies. Sustainabil-ity goals, however, strongly depend on global access to discovery-based knowledge. Yet, science-enabled technologies targeting knowledge discovery to reach sustainability goals are not in place. We propose an eco-evolutionary biology-inspired computing discovery technology for a knowledge-inspired society. We introduce evolutionary biology-inspired and artiﬁcial intelligence solutions to explore sustainability of the Seas in federated networks, networks composed by many distinct groups of individuals within species, humans and technologies exploiting resources in complex ecosystems. Knowledge discovery running on a federated network encompass a hybrid-technology to lay out the foundation of an open- and cooperative-science ecosystem for computing discovery in the face of global sustainability challenges. The project summarized here is not only set out to deliver knowledge discovery computation in federated networks, but also to provide the architecture of a science-enabled technology, as a proof-of-principle, to connect knowledge-inspired societies to global sustainability challenges.

1. Excellence

Knowledge discovery in eco-evolutionary biology-inspired federated networks ROBHOOT

**1** **Excellence**

**1.1** **Radical** **vision** **of** **a** **science-enabled** **technology**

Rapid, real time, data heterogeneity- and cooperation-based, discovery computation is currently a major issue revolving around data-driven intelligent machines and knowledge inspired societies. Several of these properties are found in evolving networks being these changes occurring in dynamic connectivity patterns and/or traits in neurons, and populations in natural ecosystems. However, evolving networks are not used for discovery computing yet, despite rapid trait evolution has been observed in experimental and theoretical systems [14, 16]. For example, evolving networks are characterized by feedbacks between the ecology and evolution of interacting traits, the eco-evolutionary feedbacks, to produce novel trait changes with new functional properties in ecosystems. This results in new computational properties, like novel interaction types (i.e., cooperation, competition, antagonism, etc), morphologies and/or evolving learning capabilities among agents to add discovery computing properties to the network. Conventional Artiﬁcial Intelligence (AI) computation is rapidly evolving towards explainable and discovery pattern inference [21] but often avoids evolutionary changes for exploring new computing capabilities [26]. The same situation occurs for artiﬁcial neural networks that also make only limited used of novel computing capabilities as a consequence of evolutionary changes in interactions and traits [28]. However, the rapid novel properties of evolving connections and traits, the diversifying power of biological systems, that make evolutionary-biology inspired networks highly plastic and resilient, have not yet been exploited in discovery computation. **The** **goal** **of** **this** **project** **is** **to** **implement** **eco-evolutionary-biology** **inspired** **solutions** **to** **make** **discovery** **computation** **a** **cooperative** **game** **of** **rapidly** **evolving** **traits** **and** **interactions**. The exploitation of evolving connections and traits will allow us to create novel types of discovery computation solutions for natural ecosystems facing sustainability challenges like overexploitation of the Seas, where harvesting renewable resources are in the point of diminishing returns for many species, communities and ecosystems (refs +++).

Why should we go deeper into evolving and diversifying information processing systems for dis-covery computation? With connections and traits (i.e., nodes and links in networks) represented in a spatially distributed network, as found in natural ecosystems, it is possible to untangle mapping of many spatiotemporal inputs onto many output functions considering learning among the interacting and heterogeneous traits and agents to decipher new solutions for harvesting renewable resources. This allows representing real-time solutions for spatiotemporal ecosystems with renewable resources, which his a key problem in many digital and natural ecosystems.

To show the capabilities of the ROBHOOT approach, we will complement the novel implementa-tions of evolutionary biology-AI discovery computation with full cycle reproducibility, automation and visualization to trigger its properties at large-scale (Figure 1). **The** **main** **impact** **of** **ROBHOOT** **is** **that** **we** **provide** **novel** **discovery** **computation** **solutions** **to** **substantially** **improve** **ecosys-tem** **sustainability** **especially** **relevant** **for** **community-rich** **digital** **and** **natural** **ecosystems**. To support this notion, we will perform eco-evolutionary biology-AI network inspired simulations of multiple data-heterogeneity based networks. The central goals of ROBHOOT are:

1. To extend existing theories of eco-evolutionary biology-AI inspired in networks to obtain under-standing of the factors and their interactions underlying discovery computation in cooperative federated networks. This will allow us to identify novel paths of reliable solutions for ecosystem sustainability.

2. To investigate how spatiotemporal evolutionary biology-AI-inspired networks can mimic the em-pirical patterns of natural and socio-technological ecosystems when large and heterogeneous ex-ploiting groups and species coexist.

3. To develop fast, reproducible and automated discovery eco-evolutionary biology-inspired compu-tation prototypes for real-time information processing tasks.

ROBHOOT 2 May 26, 2020

1.2. Science-to-technology breakthrough that addresses this vision

4. To arrive at powerful discovery computing principles for cooperative forecasting in federated networks, models of evolutionary neural biology-inspired to investigate cooperative forecasting for ecosystem sustainability when changes in learning, interactions and traits occur in a large and diverse pool of species, technologies and human groups.

Figure 1: **Discovery** **in** **Evolutionary** **Biology-Inspired** **Federated** **Networks**. ROBHOOT targets knowl-edge discovery in federated networks. Federations are composed by highly heterogeneous groups sharing ecosystem resources for a sustainable knowledge-inspired society: ROBHOOT introduces three science-enabled technolo-gies: Evolutionary biology-inspired semantic algorithms for ROBHOOT v1.0: data knowledge discovery (red), evolutionary-biology inspired AI-deep neural networks for ROBHOOT v2.0: causal knowledge discovery (green), and evolutionary neural biology-inspired ROBHOOT v3.0: discovery in federated networks

(blue).

**1.2** **Science-to-technology** **breakthrough** **that** **addresses** **this** **vision**

**Data** **knowledge** **discovery** **(WP1)**

**Evolutionary** **biology-inspired** **semantic** **algorithms** **(WP1)**: The majority of studies of data dis-covery focus on add-hoc algorithms, ignoring ecological and/or evolutionary biology-inspired solutions. Currently, only a few databases are semantically annotated (e.g. , gene ontology database, COVID-19). This is because ontology development is time-consuming, requires expert knowledge and community commitment, and is ideally paired with data-driven research that iteratively checks the soundness of the ontology as it simultaneously seeks discovery. Thus, software tools for mapping and linking the terms between diﬀerent ontologies are still to be developed, although Semantic Web technologies are included in programs such as the U.S. National Science Foundation’s proposed CyberInfrastructure (refs +++). **Going** **beyond** ROBHOOT will go beyond state-of-the-art to implement evolutionary computation concepts (i.e., genetic algorithms with diﬀerent rules and selection modes) to investigate new data prop-erties along many data-sources. ROBHOOT will provide a detailed understanding of the replicability of accounting for many data-sources on the global data architecture map contrasting diﬀerent evolutionary algorithms.

**Causal** **knowledge** **dicovery** **(WP2)**

**Eco-evolutionary** **biology-AI-inspired** **discovery** **computation** **algorithms** **(WP2)**: Many stud-ies of causal discovery (i.e., explainable or interpretable discovery), focus on genetic programming (refs +++) and symbolic regression (refs +++), ignoring eco-evolutionary biology-inspired computation

ROBHOOT 3 May 26, 2020

1. Excellence

from where causal inference can be obtained. On the other side, experimental evolution data shows the importance of rapid structural trait changes beyond plasticity for new functional information pro-cessing capabilities of the interactions and traits (refs +++). The classical view on biology-inspired information processing is to consider plasticity without structural changes, or without co-evolution among many interacting components (refs +++). Recent studies indicate that rapid trait changes and information processing as a consequence of these changes is far more complex (refs +++). For example, eco-evolutionary dynamics strongly aﬀect feedbacks between ecological and evolutionary pro-cesses, which in turn inﬂuences trait changes to open new functional properties of populations with new information capabilities (i.e., new adaptations to new habitat or niche biotic or abiotic conditions, refs +++). Furthermore, recent studies suggest that the interplay between trait dimensionality (biotic, abiotic, migration traits, etc), and adaptation is key to understand the emergence of new traits and information processing abilities to elaborate new computation strategies in ecosystems (Box 1, and refs, +++).

**Going** **beyond** ROBHOOT will, for the ﬁrst time, employ eco-evolutionary biology-inspired solutions to implement AI process-based methods to create spatiotemporal causal inference in systems containing large heterogeneity and dimensionality (Figure 2). Using the above models, this will be extended to deep process-based learning networks including trait and interactions as evolutionary changes and coevo-lution to implement diversiﬁcation patterns in these systems. The search for causal knowledge discovery will be applied to the sustainability of the Seas case study containing 9 million entries, 1612 species (around 50 variables and traits per species), around 20 countries and 11 sampling methods (Figure 2). Our approach will explore broad classes of evolving functions from evolutionary biology-AI-inspired algorithms combining them to automated Bayesian machines ensuring the search, the evaluation of mod-els, trading-oﬀ complexity, ﬁtting to the data and quantify resource usage (Deliverable D2.3, [19, 29]).

**Box** **1:** **Eco-evolutionary** **biology-AI-inspired** **discovery** **computation** **for** **sustainability** **of** **the** **Seas** **(WP2)** identiﬁes the actors, e.g., species, threats like ﬁshing pressure, environmental and habitat data and other data sources to infer causality considering evolving traits of species, technologies and the interactions to reach goal 2 (To investigate how spatiotemporal evolutionary biology-AI-inspired networks can mimic the empirical patterns of natural and socio-technological ecosystems when large and heterogeneous exploiting groups and species coexist). As an illustration purpose, diﬀerent Gears across countries aﬀects the spatial and temporal samplings and the distribution of ﬁsh species. The consequence of the distribution of abundance/catches of Megrim and Haddock is strongly aﬀected by the choice of gears by the Irish and the Spanish ﬂeet (Figure 2). A social group represents a set of actors with multiple traits. In this context, groups can be represented with evolving environmental and technological traits. This can be formally described as a distribution-ﬁshery cooperation-competition matrix, C2, as follows:

2 DA*g,*B*g* (*c*) DA*g,*B*g* (*nc*)

FA*g,*B*g* (*c*) c(*ϕ*)

nc(Φ*Ag* *,*Φ*Bg* )*,c*(*γ*)

FA*g,*B*g* (*nc*) ! c(Φ)*,nc*(*γAg* *,γBg* )

nc(*φAg* *,φBg* )

where D, F, *i*, A*g*, B*g*, c and nc, represent distribution map and ﬁshery of species *i*, group *g* within country A and B, cooperation and non-cooperation, respectively. The evolutionary biology-inspired functions represent environmental and technological traits with diﬀerent degrees of complexity in the C2 matrix: If the two groups within the countries cooperate, *c*(*ϕ*), then the environmental and technological rate change, *ϕ*, is synchronized between groups to evolve towards decreasing Gear bias and make distribution maps and the ﬁshery sustainable. On the other side, if the two groups decide not to cooperate, *nc*(*φAg* *,φBg* ), then there is environmental and technological rate change, *φAg* and *φBg* with each group following changes of their own gears, the GOV for the Ireland group and the Baka Gear for Spain group, independently of the other and as a function of their ﬁshery interest. There is no interest in decreasing bias in species distribution maps making ﬁshery non sustainable in this case. In the last two scenarios groups enter in cooperation for the distribution map of species *i*, but not in the ﬁshery (*c*(Φ)*,nc*(*γAg* *,γBg* )), or they do cooperate in the Fishery for species *i* but not for the distribution map of species *i* (*nc*(Φ*Ag* *,*Φ*Bg* )*,c*(*γ*)). The situation for cooperation in the distribution maps follows agreements between the two groups to technological changes in the Gear but still preserving their GOV and the Baka Gears for ﬁsheries.

**Discovery** **in** **federated** **networks** **(WP3)** Integrating data and causal knowledge graphs provide a mechanistic understanding of how the balance of cooperation vs. competition might alter sustainabil-

ROBHOOT 4 May 26, 2020

1.3. Interdisciplinarity and non-incrementality of the research proposed

ity in our exploration of the Seas case study. However, causal knowledge graphs are not enough if they only represent isolated contributions and can not “learn to learn” to ﬁnd novel, emergent solutions in neural biology-inspired networks composed by highly heterogeneous groups. In this regard, federated objects can be seen as “neural networks” containing many types of heterogeneous nodes with varying degrees of learning, connectivity and ﬁring probabilities [22, 23]. Technologies in digital ecosystems around federated networks are scarce and mostly focus on decentralization, scalability and security fronts [7, 8, 12, 13, 18, 24]. In the science ecosystem, only a few applications of open decentralized technologies exist [20]. Yet, the discovery of novel algorithms in biology-inspired federated networks for cooperative forecasting of global sustainability problems when heterogeneous groups learn and share from each other is currently not in place. Recent studies have shown the importance of evolutionary search of mathematical and symbolic operations as building blocks to discover ML algorithms ([19, 26]). Evolutionary biology-inspired search for algorithmic discovery can help to decipher how interactions among heterogeneous groups evolve and learn to solve complex sustainability problems. For example, evolutionary dynamics can explore open-ended language of models with varying trait evolution func-tions to discover biologically inspired solutions in multidimensional systems ([26],+++). ROBHOOT v.3.0 deploys biology-inspired federated networks accounting for heterogeneous agents to discover novel biology-inspired solutions for the exploration of the Seas federated network (Deliverables D3.1 and D3.2, Tables 3.1a-c)

**Going** **beyond**: Our understanding of the outcomes from evolved information processing systems formed by highly heterogeneous groups, a kind of large-scale meta-learning in the federated setting [12], is currently quite limited. Therefore, new science-enabled approaches accounting for information processing with diversiﬁcation of heterogeneous and highly dimensional systems in federated networks are required to develop science-enabled technologies where heterogeneous agents with diﬀerent interests ﬁnd (non optimal) solutions that allow sustainable explotation of ecosystms. ROBHOOT v.3.0 con-nects knowledge discovery to biology-inspired federated netwoks to study the properties of cooperative forecasting and strong inference in the face of global sustainability and biodiversity challenges (Figure 2 and Tables 3.1.a-c).

**1.3** **Interdisciplinarity** **and** **non-incrementality** **of** **the** **research** **proposed**

To succeed with ROBHOOT, it is essential to build an interdisciplinary team that includes scientists from diﬀerent disciplines, including evolutionary biology, ecology, computational neuroscience, computer science, data science, complex systems and experts in biodiversity sampling methods and the infras-tructure related to international protocols for sampling the Seas. Data knowledge discovery gained by analysis and modelling of the computation discovery capabilities of evolutionary-inspired semantic algorithms by the evolutionary biology, computer science and complex system members of this con-sortium (EBD-CSIC, IFISC-CSIC, SDSC) can be transferred to the causal domain addressed by the other part of the consortium with expertise in evolutionary biology, data science and causal inference (EAWAG and TARTUR). This will be enriched with full automation, reproducibility and visualiza-tion supported by ICREA, SDSC, and our company-partner (SME), respectively. Conversely, those scientists working on neurobiology and eco-evolutionary dynamics in ecosystems will feed information back on fundamental discovery computational challenges in federated networks (i.e., role of heterogene-ity, evolving traits and interactions, cooperation, learning functions, and dimensionality) encountered in their implementations to explore to what degree this is reﬂected also in eco-evolutionary biology-inspired and neurobiology inspired discovery computation models to augmented their models. This cross-fertilizing back-and-forth interaction will allow the project to keep high modularity within the work packages while keeping functional interactions among the groups to run eﬃciently the diﬀerent stages of the project. To bring together adaptive biology-inspired semantic algorithms for data discov-ery and evolutionary-neurobiology-inspired discovery in federated networks requires a long stride and this has not been attempted so far. This way, we expect to realize a truly novel, sustainability-driven knowledge-inspired society technology for which there are no predecessors. Thus, ROBHOOT will

ROBHOOT 5 May 26, 2020

1. Excellence

not be incremental, but a leap opening a new direction for eco-evolutionary biology-inspired discovery computation.

**Box** **2:** **Eco-evolutionary** **neurobiology-inspired** **discovery** **computation** **for** **sustainability** **of** **the** **Seas** **in** **federated** **networks** **(WP3)**: Evolutionary algorithms might trigger novel algorithmic ﬁndings, the discovery knowledge graphs, and ... RHv.3.0 introduces “Cooperative Forecasting” as evolutionary biology-inspired neural learning algorithms for the discovery of new solutions in large federated networks (Tables 3.1a-c). RHv.3.0 search for how learning among interacting heterogeneous groups discover evolutionary algorithms and in our exploration of the Seas case study this can be represented as follows: Now the focus is on cooperative learning to discover new solutions. For example, how learning from the most distant strategies in the technological and environmental traits can make distribution catchability maps similar. Groups can now be represented not only as environmental and technological traits, but with evolving learning traits as a function of the distance between each pair of groups sharing resources. This can be formally described as a distribution-ﬁshery cooperation learning matrix C2, as follows:

2 DA*g,*B*g* (*c*) DA*g,*B*g* (*nc*)

FA*g,*B*g* (*c*) c(*ϕ,*L*d*)

nc(Φ*Ag* *,*Φ*Bg* )*,c*(*γ,*L*d*)

FA*g,*B*g* (*nc*) ! c(Φ*,*L*d*)*,nc*(*γAg* *,γBg* )

nc(*φAg* *,φBg* )

where D, F, *i*, A*g*, B*g*, c and nc, represent distribution map and ﬁshery of species *i*, group *g* within country A and B, cooperation, and non-cooperation, respectively, as in ROBHOOT v.2.0. In addition, we introduce learning functions depending of the distance between two groups, L*d*. We will search evolving learning functions that can be coupled to environmental and technological traits with diﬀerent degrees of complexity in the C2 matrix: If the two groups within the countries are suﬃciently distant, then learning functions play a role to cooperate, *c*(*ϕ,*L*d*), and the environmental and technological rate change, *ϕ*, strongly depend on learning between the interacting groups making distribution maps and the ﬁshery more sustainable.

(Write from here how the learning scenario can enter in the non-cooperative strategies) On the other side, if the two groups decide not to cooperate, *nc*(*φAg* *,φBg* ), then there is environmental and technological rate change, *φAg* and *φBg* with each group following changes of their own gears, the GOV for the Ireland group and the Baka Gear for Spain group, independently of the other and as a function of their Fishery interest. There is no interest in decreasing bias in species distribution maps making ﬁshery non sustainable in this case. In the last two scenarios groups enter in cooperation for the distribution map of species *i*, but not in the Fishery (*c*(Φ)*,nc*(*γAg* *,γBg* )), or they do cooperate in the Fishery for species *i* but not for the distribution map of species *i* (*nc*(Φ*Ag* *,*Φ*Bg* )*,c*(*γ*)). The situation for cooperation in the distribution maps follows agreements between the two groups to technological changes in the Gear but still preserving their GOV and the Baka Gears for Fisheries.

**1.4** **High** **risk,** **plausibility** **and** **ﬂexibility** **of** **the** **research** **approach**

ROBHOOT represents a novel approach for complex, adaptive and multidimensional discovery computa-tion. The transfer of eco-evolutionary biology-inspired principles onto fully reproducible and automated software, progressing from fragmented- and pattern-based to integrated- and process-based discovery technology, will be a major qualitative step, deﬁning ROBHOOT as a high-risk project, ﬁtting into FET-Open. To achieve the ambitious goals, we will combine expertise from all involved areas, mitigat-ing risk in a gradual way, following a strict line and gradually increasing in complexity of the problems addressed. Figure 3 shows that we will start with evolutionary biology-inspired semantic algorithms for data discovery in the context of the Sustainability of the Seas case study. This is followed by inves-tigation and implementation of more complex eco-evolutionary biology-inspired AI and deep learning network modeling to infer causality in the sustainability of the Seas case study (i.e., dimensionality, nonlinearities). Then we will advance to more complex situations, where the evolutionary neurobiology-inspired modeling will expand the search along many learning and cooperative forecasting schemes to ﬁnd scenarios for the sustainability of the Seas case study. To keep the project technically feasible, and to be able to identify the mechanisms and their properties from data and causal discovery computation to discovery in federated networks, we will limit methods to three main approaches. All of the above

ROBHOOT 6 May 26, 2020

1.4. High risk, plausibility and ﬂexibility of the research approach

will be done by combining theoretical work and numerical simulations with a real empirical case for the Sustainability of the seas. The knowledge gained along these three lines will allow us to compactly represent all the steps into a uniﬁed science-enabled technology. This leaves open the option to work with fast computing languages to develop low-level Agent Based Models along all the theoretical devel-opment of the proposal (i.e., Julia, C++), instead of diﬀerential/diﬀerence equations methods when a large number of agents and interactions change in time and space. This feature represents a very de-sirable fallback in case of speed and convergence problems for multidimensional and nonlinear systems (Table 1.41 Critical risks for implementation). Our implementation activities are all complemented by numerical investigations contrasted for speed and robustness with the sustainability of the Seas case study started in 1965 and containing around 9 million entries, 1612 species, 20 countries and 11 sampling methods (Figure 2). The success of ROBHOOT would represent a breakthrough in the current discov-ery computation with direct application to sustainability of ecosystems. It exploits eco-evolutionary biology-inspired computational capabilities of evolving traits and interactions to discovery and transfers their properties to natural ecosystems. The combination of rapid, data heterogeneity and cooperation for discovery computation based on, mostly open-source languages, will lead to fast implementations of the demonstrators with high ﬂexibility that will permit a rapid transit to the public.

**Table** **1.4a:** **Critical** **risks** **for** **the** **research** **approach**

|  |  |  |  |
| --- | --- | --- | --- |
| **Description** **of** **risk** | **Objective** | **WP** | **Proposed** **risk-** **mitigation** **mea-sures** |
| Evolutionary semantic algorithms insuﬃciently developed: Medium | 2 | WP1 | Consider more developed genetic programming methods to infer data interactions. |
| Multilayer metrics accounting for spatiotemporal patterns along many datasets insuﬃciently developed: Low | 2 | WP1 | Implementation of more standard complex networks metrics to charac-terize data knowledge discovery. |
| Low number of training data avail-able: Medium | 2,3 | P2 | Alternative methods focusing on ma-trix decomposition methods. |
| Automated evolutionary-inspired expressions for causal knowledge discovery insuﬃciently developed: Medium | 2,3 | WP2 | Symbolic regression methods to full automation for causal discovery ac-counting for evolutionary rules. |
| Eco-evolutionary dynamics of multi-ple traits in species-rich ecosystems insuﬃciently developed: Medium | 1-4 | WP3 | Mean-ﬁeld approximations using classicalODEsystemsandnoveluni-versal diﬀerential equations for sci-entiﬁc machine learning. |
| Evolutionary neurobiology-inspired federated networks insuﬃciently de-veloped: Medium | 1-4 | WP3 | Spiking neural network models as alternatives to evolutionary neural biology-inspired algorithms in feder-ated networks. |
| Cooperative forecasting mixing eco-evolutionary dynamics and neu-ral nets in large scale federated networks insuﬃciently developed: Medium | 1-4 | WP3 | Mix eco-evolutionary dynamics models with less alternative neural nets models working a smaller spatiotemporal scales. |

ROBHOOT 7 May 26, 2020

2. Impact

**2** **Impact**

**2.1** **Expected** **impact**

• **Scientiﬁc** **and** **technological** **contribution** **to** **the** **foundation** **of** **a** **new** **future** **technology**: ROBHOOT targets novel approaches towards sustainable ecosystems. One of the tasks in WP3 focus on the discovery of novel evolutionary neurobiology-inspired algorithms to provide results for sustainability ﬁsheries. Solutions around WP3 ultimately depend on merging WP3 with the rest of WP’s in the proposal. For example, it is known that sustainable ecosystems strongly depend on many data sources collected by diﬀerent groups using diﬀerent technologies (refs +++). ROBHOOT discover data interactions combining ﬁsheries, stakeholders, and technology data, the data knowledge discovery graph, as a ﬁrst step towards the discovery process. ROBHOOT also infer the technological and environmental changes and the processes underlying the empirical patterns, the causal knowledge discovery, to provide the existing sustainability status in a human-disturbed ecosystem. Altogether, this project will lay the foundation for future sustainability studies. Discovery of novel evolutionary-inspired algorithms for biodiversity maintenance have been hardly been investigated in this context so far. Therefore, several predictors related to biodiversity, technological and social times series analysis will be tested and further developed to enable robust prediction of sustainability. The discovery of new solutions not observed in the empirical data, but containing plausible scenarios for maintaining species-rich and sustainable ecosystems, will be the basis for estimation of the severity of overﬁshing and sampling bias when many groups enter in commercial conﬂict of interest... Such a targeted sustainability proxies would be of great interest not only for the biodiversity maintenance but also from an economic and social point of view, as it would save costs for future generations. Sustainability challenges are related to the development of future sustainable societies, which according to (Organization...) **Keep** **elaborating**

• **Potential** **for** **future** **social** **or** **economic** **impact** **or** **market** **creation**: Collapse of ecosys-tems can lead to serious long term economic and ecological disfunctionalities (refs +++). How-ever, there are not well established metrics for the characterization of sustainability in complex ecosystems. Our approach accounts for heterogeneous sources of data, the (evolving) mechanisms underlying technological, environmental and social changes required to make ecosystems sustain-able and novel rules that could impact positively the maintenance of biodiversity by developing cooperative forecasting strategies among the many (international) groups involved. Such a risk assessment would not only be of great interest to the groups exploiting the resources, but also from an economic and ecological point of view, as having less bias in the ﬁeld data provides more accurate measures from the observed time series for planning ﬁsh stocks for a large number of species. Finally, ROBHOOT contributes towards knowledge-inspired societies in need of radically tackling new societal and global environmental challenges: it provides reproducible and transpar-ent methods for making sustainability goals achievable and reproducible across many sectors and economies.

In the medium-term this technology may also have interesting applications in public and pri-vate industry. For example, access to discovery with cooperative forecasting might suggest new paths and solutions that are key to generate rapid and robust scenarios when facing complex problems including global sustainability challenges (i.e., global health, ecosystems degradation,

ROBHOOT 8 May 26, 2020

2.1. Expected impact

biodiversity loss, etc). First, evolutionary biology-inspired AI algorithms deciphering open-ended search of interpretable mechanisms underlying the targeted complex systems for private and pub-lic industry facing highly heterogeneous data sources. Second, cooperative forecasting challenges existing fragmented responses to emergent global sustainability problems by compactly oﬀering reproducible forecasting emerging from many-to-many human and machine cooperative discov-ery, and third, open-access explainable and automated information generation account for global data-arquitecture allowing individuals and companies to address scenarios of future strategies in highly ﬂuctuating local and global market conditions.

• **Impact** **on** **transparency** **and** **reproducibility**: Decision making and governance at local, regional and global scales require access to transparent and reproducible information containing the interpretable factors and their plausibility to explain the empirical patterns. In this regard, the ROBHOOT consortium brings together excellent partners from the ﬁelds of computer sci-ence, neurobiology, complex system, biology, social sciences, evolutionary ecology and including one SME focusing on reproducibility, automation, visualization and reporting along its whole developmental life cycle (Dissemination plan below and Figure 3). At the same time, all groups composing the consortium exhibit a long-standing experience interdisciplinary research across the boundaries of the individual disciplines (Figure 3). The subsection on related projects shows that this is a novel constellation in Europe and possibly worldwide (section 4). This consortium is also at the leading edge of developing novel evolutionary biology-AI inspired solutions to automation and reproducibility in complex systems facing sustainability challenges.

• **Ecosystem** **health** **impact**: Ecosystem sustainability and ecosystem health are usually used as metaphors to describe the mechanisms that maintain functional and diverse systems and the condition of an ecosystem, respectively. Ecosystem sustainability and condition can vary as a re-sult of many disturbances like ﬁre, ﬂooding, drought, extinctions, invasive species, climate change, mining, overexploitation in ﬁshing, farming or logging, chemical spills, and a host of other reasons. ROBHOOT focus on novel discovery solutions for ecosystems under a varying degree of distur-bances. ROBHOOT introduces a case study for overexploited ocean ecosystems when highly heterogeneous social groups with diﬀerent interests exploit limited and shared resources. Thus, ROBHOOT is a technology designed to provide novel discovery solutions paths for ecosystem sus-tainability, improving the underlying discovery paths that allow draw novel connections between ecosystem sustainability and ecosystem health. This feature aligns to the EU Reﬂection paper towards a Sustainable Europe by 2030 focusing on the need of investing in sustainable growth and spur action by goverments, institutions and citizens, leading the way for the rest of the world using the UN’s Sustainable Development Goals (SDGs). Speciﬁcally, ROBHOOT can be seen as an horizontal enabler for the sustainability transition to make Europe sustainable by 2030. It introduces evolutionary biology- and artiﬁcial intelligence-inspired solutions to beneﬁt ecosystem health and people’s lives and work. By being able to process large amounts of heterogeneous data instantaneously, artiﬁcial intelligence and evolutionary-biology inspired solutions have the poten-tial to signiﬁcantly increase productivity in environmental sustainability and ultimately make informed decisions to enhance food security [1].

• **Building** **leading** **research** **and** **innovation** **capacity** **across** **Europe**: This consortium brings together excellent partners from the ﬁelds of computer science, machine learning, deep learning networks, neurobiology, complex systems, experimental biology, biology and evolutionary ecology and in particular evolutionary biology-inspired federated networks both from a theoretical and an experimental point of view, Physics, theory and applications of complex systems in social networks and one highly innovative science-based reproducibility, automation, reporting and com-munication focusing on sustainability solutions. Many of the components of the consortium are ﬁrst-time participants to FET under Horizon 2020 (Section 4). The use of advanced evolutionary biology-inspired and complex networks-based analyses to characterize and predict novel discov-

ROBHOOT 9 May 26, 2020

2. Impact

ery in systems formed by heterogeneous and evolving groups and interactions combined with the implementation of intelligent learning discovery in federated networks and the development of a reproducible and automated protocol user friendly interface go much beyond the current state-of-the-art in science-based discovery technologies. All consortium partners exhibit a long-standing experience in interdisciplinary research across the boundaries of the individual disciplines (Figure 3). The subsection on related projects shows that this consortium is at the leading edge of in-novation and interdisciplinarity (Tables 3.1a-c). A signiﬁcant value proposition of the project is to increase the research on large-scale sustainable federated networks where many heterogeneous agents share resources embedded in complex ecosystems. This will produce valuable information and data about how federated networks work under broad set of socio-ecological scenarios, similar to natural ecosystems consoritiums where many paths produce coexistence of heterogneous pop-ulations and high biodiversity (refs ++). It is important to consider that all ecosystems facing many human pressures are all across the world and discovery technologies facilitating the solutions in large-scale federated networks could inspire new developments improving our understanding of sustainability at global scale. For in-home, we also expect an explosion of discovery knowledge ap-proaches and future publications, which will place Europe at the top of sustainability in federated networks.

Moreover, in WP3, we propose the generation of a web-based sustainability discovery portal that will allow researchers, NGO, managers and the public to train students in the discovery process to manage over-exploited ecosystems, allowing to scale up the number of people participating in the sustainability process by an order of magnitude thus mobilising forward thinking researchers and excellent young researchers to work together and explore what may become a new technol-ogy paradigm in sustainability research. Members of the consortium already have experience in generating such types of training tools that are currently available online (check github repository RobhooX). This approach would provide an unprecedented capability for the access to a multi-tude of people interested in sustainability discovery tools that will result in facilitating consensus and a valuable source of information for science-enabled technologies in ecosystem sustainability and management.

**2.2** **Measures** **to** **maximize** **impact**

**Dissemination**

• **The** **Plan** **for** **diseminating** **and** **exploiting** **the** **project** **results**: ROBHOOT allocates three research groups along its whole developmental life cycle to guarantee dissemination, transparency and easy exploitation of the technology **(when)**. **(what)** The three milestones of the project, data knowledge discovery, causal knowledge discovery and discovery in federated networks (Ta-ble 3.2a) will be fully automated and reproducible to facilitate visualization, reporting and full scalability. **(who)** Automated discovery will be implemented along Bayesian machine scientist to facilitate open-ended search during the development of the three milestones (Tables 3.1a-b). Reproducible knowledge discovery graphs will be developed in the Renku open-source software (Swiss Data Science Center, SDSC). Visualization and reporting will be fully implemented in the Julia computing language for its speed and unique features (SME, Codes will be available in the public git [Robhoot](https://github.com/RobhooX/Robhoot) repository. Having the whole developmental life cycle as reproducible and au-tomated knowledge discovery graphs facilitates the reuse and the dissemination of the technology as a whole in any platform and OS. Full reproducibility, automation, visualization and reporting provide to ROBHOOT legal and ﬁnancial transparency and reproducibility in social governance a feature for easy replication of the discovery process by third parties, a property that can be used to facilitate reporting for governance public policy, NGO, society and thinktank in the face of local and global sustainability challenges. **why,** **how** **and** **which** **journals,** **conferences** **and** **with** **which** **preliminary** **results**.

ROBHOOT 10 May 26, 2020

2.2. Measures to maximize impact

• All the data, codes and outputs generated during ROBHOOT development will be open access stored in public git repositories. The project will collect data from many sources (i.e., ﬁsheries, environmental and social data, technology data). generate data knowledge discovery graphs, causal knowledge graphs and the data and algorithms generated from the discovery in federated networks for the sustainability of the Seas case study **Keep** **elaborating**

**Communication** **activities**

• The full open-source developmental life cycle strategy of reproducibility, automation, and report-ing generation of ROBHOOT targets the search of societal relevance and long-term economic impact of open and transparent science. Underlying to this strategy is to build support for future research and innovation funding, by ensuring uptake of results within the scientiﬁc community, and opening up potential business opportunities for novel products or services, and potentially contributing to better decision-making processes and valuable input for public policies formula-tion. ROBHOOT has very general dissemination targets, from scientists and decision-makers, to the business community and the public. ROBHOOT’s general dissemination measures will focus on project results and stakeholder engagement (stakeholder consultation processes; workshops to raise awareness, etc.) through:

. The project website is to be set up within the ﬁrst three months of the project. There is already a public git [Robhoot](https://github.com/RobhooX/Robhoot) repository.

. Up to date information material, e.g. brochures, presentationslides, will be distributed at events to increase awareness about the ROBHOOT project.

. General other publication means will be used such as newspapers, YouTube, TV and radio, social networks as well as targeted mailing lists (e.g., evodir, AI-worldwide).

Scientiﬁc publications for the scientiﬁc community. We will target high-level journals with open access (i.e., Science, Nature Communication, etc.)

. The consortium will visit conferences in the related scientiﬁc ﬁelds and interdisciplinary con-ferences in order to interactively present and discuss our results with others researchers, groups and institutions. Among other activities, the consortium will organize special sessions at several conferences in diﬀerent countries. Additionally, some targeted, speciﬁc dissemination actions will be considered: We will organize hackatons and robhacks activities to attract multipliers and de-velopers from the open-source community to the community who engage in data processing and build hybrid evolutionary biology-inspired and AI algorithms. This will be achieved by a “trav-eling salesman” approach using personal visits and invitations to demonstrate how ROBHOOT works. At the end of the project we will organize a workshop speciﬁcally on “Evolutionary-biology AI inspired solutions for global sustainability challenges” for disseminating our results to a broad set of groups and experts in ﬁelds related to global sustainability for assessing future exploitation potential, inviting partners from academia as well as industry.

. ROBHOOT will launch a testnet to help disseminate the main results of discovery in federated networks (Section 3.1.3). The launch will have invited NGO’s and GO across disciplines and social, economical and technological sectors. The ROBHOOT Open Discovery Network will be launched as a Biodiversity and sustainability open discovery network to oﬀer the solutions for the explo-ration of the Seas case study and to integrate additional public databases and data collections into the open discovery network to facilitate NGOs, GOs and other organizations transparency, reproducibility, and governance in Biodiversity management.

• ROBHOOT strictly adheres to the Open Access Policy of the Commission and all publishable (non-protected) results will follow the green or gold OA policy. Software as well as hardware protocols will be made openly available through standard computer science repositories. The ROBHOOT public git repository is already active [Robhoot.](https://github.com/RobhooX/Robhoot) Data (measured data), as such, will not be acquired by ROBHOOT. Open-source codes and analysis of standardized inputs/outputs

ROBHOOT 11 May 26, 2020

3. Implementation

and software will be made public through an online platform with the aim of converting it in The Reference Point for any future research in knowledge discovery. Open access to publications will be granted under the terms and conditions laid down in the Grant Agreement, in accordance with the Rules for participation and dissemination in Horizon 2020. The beneﬁciaries will deposit an electronic copy of the published version or the ﬁnal manuscript accepted for publication of a scientiﬁc publication relating to foreground in an institutional or subject-based repository at the moment of publication, e.g., via the OpenAIRE portal (www.OpenAIRE.eu). In addition, beneﬁciaries will make their best eﬀorts to ensure that this electronic copy becomes freely and electronically available to anyone through this repository (i.e., that it becomes “open access”): immediately, if the scientiﬁc publication is published “open access”, i.e., if an electronic version is also available free of charge via the publisher, or within 6 months of publication.

**3** **Implementation**

**3.1** **Research** **methodology** **and** **work** **plan,** **work** **packages** **and** **deliverables**

The project consists of ﬁve work-packages (WP1-WP3: R&D, WP4: Dissemination and WP5: Manage-ment). WP1 deals with evolutionary semantic algorithms for data knowledge discovery, WP2 addresses evolutionary biology-AI-inspired models to infer causal knowledge discovery with an implementation for the exploration of the Seas case study, WP3 addresses evolutionary neural biology-inspired for knowl-edge discovery to provide cooperative forecasting in federated networks. WP3 also provides a empirical case implementation of cooperative forecasting for the exploration of the Seas.

**Demonstrators**: The project will create three demonstrators of increasing complexity all containing

full reproducibility and automation capabilities:

• RHv1.0 Software demonstrator with evolutionary semantic algorithms to decipher ontologies

along many data-sources for the exploration of the Seas data knowledge discovery case study

(MS1);

• RHv2.0 Software demonstrator with evolutionary biology-AI-inspired modeling for spatiotempo-

ral causal pattern knowledge discovery (MS2);

• RHv3.0 Software demonstrator using evolutionary neural biology-inspired networks for spatiotem-

poral discovery in federate networks (MS3).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table** **3.1a**: **List** **of** **work** **packages** | | | | | | |
| **Work** **pack-age** **No.** | **Work** **package** **title** | **Lead** **No.** | **Lead** **Short** **Name** | **PMs** | **Start** **Month** | **End** **Month** |
| 1 | Data knowledge discovery | 1 | CSIC | XX | 1 | 18 |
| 2 | Causal knowledge discovery | 6 | TARTU ULIKOOL | XX | 7 | 24 |
| 3 | Discovery in federated networks | 9 | UNIGRAZ | XX | 13 | 36 |
| 4 | Dissemination | 10 | IEO | XX | 1 | 36 |
| 5 | Management | 6 | EAWAG | XX | 1 | 36 |
|  |  |  | Total PMs | XXX |  | |

The inference of causal mechanisms and the discovery of spatiotemporal patterns in federated net-works is a generic problem found in e.g. many agents sharing resources, sustainability, eco-evolutionary networks, biodiversity maintenance, or social networks. Thus, the discovery computation of spatiotem-poral patterns represents an ubiquitous computational problem in digital and natural ecosystems, where many evolving and heterogeneous agents and interactions share information to reach sustainability goals. In the demonstrators of ROBHOOT , we will consider at least diﬀerent scenarios for each of the software implementations such that agents contain many evolving traits and interactions can also evolve along diﬀerent signs and eﬀects (M1, M2 and M3). This allows, for example, ﬁnding trait and interaction changes patterns that improve sustainability scenarios with respect to the observed empirical patterns in the exploration of the Seas case study. In the course of the project, more complex context-dependent

ROBHOOT 12 May 26, 2020

3.1. Research methodology and work plan, work packages and deliverables

trait changes of agents and interactions together with diﬀerent learning functions will be considered to explore how they aﬀect sustainability properties in federated networks.

Gantt chart:(M=Milestone,D=Deliverable,R=Project Reporting,T=Task)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **YEAR** |  | | | | | | | | | **2021** | | | | **2022** | | | | **2023** | | | |
| **MONTH** |  | | | | | | | | | **Q1** | **Q2** | **Q3** | **Q4** | **Q1** | **Q2** | **Q3** | **Q4** | **Q1** | **Q2** | **Q3** | **Q4** |
| **MILESTONE** |  | | | | | | | | |  |  |  |  |  |  |  | **M1** |  | **M2** |  | **M3** |
| **WP** | **WP** **Name** | **PROGRESS** | | | | | | **START** | **END** |  |  |  |  |  |  |  |  |  |  |  |  |
| **WP1** | **Data** **knowledge** **discovery** **(DKD)** |  | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| T1.1 | Evolutionary semantic algorithms |  | 17% | | | | | 1/1/21 | 31/06/22 |  |  |  |  |  | **D1.1** |  |  |  |  |  |  |
| T1.2 | Multilayer network metrics |  | | 34% | | | | 1/1/21 | 31/06/22 |  |  |  |  |  | **D1.2** |  |  |  |  |  |  |
| T1.3 | Automation DKD | 51 | | | % | | | 1/4/22 | 1/8/22 |  |  |  |  |  |  | **D1.3** |  |  |  |  |  |
| T1.4 | Reproducibility DKD | 68% | | | |  | | 1/8/22 | 1/13/22 |  |  |  |  |  |  | **D1.4** |  |  |  |  |  |
| T1.5 | Visualization DKD | 85% | | | | |  | 1/2/21 | 1/4/21 |  |  |  |  |  |  | **D1.5** |  |  |  |  |  |
| T1.6 | Data knowledge discovery EX | 100% | | | | | |  |  |  |  |  |  |  |  |  | **D1.6** |  |  |  |  |
| **WP2** | **Causal** **knowledge** **discovery** **(CKD)** |  | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| T2.1 | Eco-Evolutionary AI Algorithms |  | 17% | | | | | 1/3/21 | 1/7/21 |  |  |  |  |  |  |  | **D2.1** |  |  |  |  |
| T2.2 | Eco-Evolutionary Deep Learning |  | | 34% | | | | 1/5/21 | 1/10/21 |  |  |  |  |  |  |  | **D2.2** |  |  |  |  |
| T2.3 | Automation CKD | 51 | | | % | | | 1/10/21 | 1/13/21 |  |  |  |  |  |  |  |  | **D2.3** |  |  |  |
| T2.4 | Reproducibility CKD | 68% | | | |  | |  |  |  |  |  |  |  |  |  |  | **D2.4** |  |  |  |
| T2.5 | Visualization CKD | 85% | | | | |  | 1/10/21 | 1/12/21 |  |  |  |  |  |  |  |  | **D2.5** |  |  |  |
| T2.6 | Causal knowledge discovery EX | 100% | | | | | | 1/10/21 | 1/13/21 |  |  |  |  |  |  |  |  |  | **D2.6** |  |  |
| **WP3** | **Discovery** **in** **federated** **networks** **(DFN)** |  | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| T3.1 | Sharing federated networks |  | 17% | | | | | 1/16/21 | 1/21/21 |  |  |  |  |  |  |  |  |  | **D3.1** |  |  |
| T3.2 | Evolutionary neural networks |  | | 34% | | | | 1/22/21 | 1/26/21 |  |  |  |  |  |  |  |  |  |  |  | **D3.2** |
| T3.3 | Automation DFN | 51 | | | % | | | 1/27/21 | 2/1/21 |  |  |  |  |  |  |  |  |  |  |  | **D3.3** |
| T3.4 | Reproducibility DFN | 68% | | | |  | | 2/2/21 | 2/6/21 |  |  |  |  |  |  |  |  |  |  |  | **D3.4** |
| T3.5 | Visualization DFN | 85% | | | | |  | 1/27/21 | 1/31/21 |  |  |  |  |  |  |  |  |  |  |  | **D3.5** |
| T3.6 | Discovery in federated networks EX | 100% | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  | **D3.6** |
| **WP4** | **Dissemination** |  | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| T4.1 | Dissemination activities |  | 17% | | | | | date | date |  |  |  | **D4.1** |  |  |  | **D4.2** |  |  |  | **D4.5** |
| T4.2 | Analysis Exploitables |  | | 34% | | | | date | date |  |  |  |  |  |  |  |  |  |  |  |  |
| T4.3 | Business plan | 51 | | | % | | | date | date |  |  |  |  |  |  |  |  |  |  |  | **D4.6** |
| T4.4 | Hackaton Robhoot 1.0 | 68% | | | |  | | date | date |  |  |  |  |  |  |  | **D4.3** |  |  |  |  |
| T4.5 | Data management | 85% | | | | |  | date | date |  |  |  |  |  |  |  | **D4.4** |  |  |  |  |
| T4.6 | Exploration of the Seas outreach | 100% | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  | **D4.7** |
| **WP5** | **Management** |  | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| T5.1 | Project initiation | 50 | | | % | | | date | date |  |  |  |  |  |  |  |  |  |  |  |  |
| T5.2 | Other management task (R = Reporting) | 100% | | | | | | date | date |  |  |  | **R** |  |  |  | **R** |  |  |  | **R** |

ROBHOOT 13 May 26, 2020

3. Implementation

**Table** **3.1b**: **Work** **package** **description** Please note that the basic technical considerations for the setups are described in side boxes...

|  |  |
| --- | --- |
| **Work** **package** **number** **1** **Lead** **beneﬁciary** **EBD-CSIC** | |
| **Work** **package** **title** | **Data** **knowledge** **discovery** |
| **Participant** **number** | 1 2 3 4 5 |
| **Short** **name** **of** **participant** | EBD-CSIC IFISC-CSIC ICREA SDSC SME |
| **Person** **month** **per** **participant** | 9 6 3 3 3 |
| **Start** **month** **End** **month** | 1 24 |

**Objectives**

• Develop a evolutionary semantic framework for data discovery

• Derive semantic functionality rules required for data computation discovery

• Adaptive learning rules and metrics for the sustainability of the Seas data discovery

**Description** **of** **work**

**Task** **T1.1:** **Develop** **evolutionary** **semantic** **algorithms** **to** **investigate** **data** **extraction** **and** **transformation** **in** **ontologies** **(M1-M18)** *Leader:* ***EBD-CSIC****.* *Contributors:* *1* Evolutionary driven ontologies will be mapped to a graph-based data architecture ﬂexible enough to get high scalability (i.e. Neo4j) and to infer multilayer metrics (T1.2). Currently software tools for mapping and linking the terms between diﬀerent ontologies are still to be developed [5] and/or avoid adaptive algorithms for doing data extraction and transformation (refs ++, add as ref Semantic Web technologies are included in programs such as the U.S. National Science Foundation’s proposed CyberInfrastructure). T1.1 provides adaptive algorithms to allow WP2 and WP3 to implement this feature in causal knowledge discovery and discovery in federated networks. Miguel: Keep elaborating

**Task** **T1.2:** **This** **task** **extends** **T1.1** **into** **multilayer** **network** **metrics** **for** **general** **princi-ples** **of** **data** **discovery** **(M1-M18)** *Leader:* ***IFISC-CSIC****.* *Contributors:* *2* Multilayer network metrics [9, 11] for evolutionary semantic algorithms will focus on large pools of data heterogeneity to explore how data conﬁgurations, privacy requirements, formats, dimensions, biases and spatiotemporal resolution aﬀect data discovery [2–4, 6]. Victor, Emilio: Keep elaborating

**Task** **T1.3:** **Based** **on** **the** **framework** **developed** **in** **T1.1** **and** **T1.2,** **ICREA** **will** **derive** **automation** **rules** **for** **data** **discovery** **(M15-M21)** *Leader:* ***ICREA****.* *Contributors:* *3* Automation rules [19] for evolutionary semantic algorithms and multilayer network metrics search and rules transformation for data discovery. Roger: Keep elaborating

**Task** **T1.4:** **Reproduce** **(M15-M21)** *Leader:* ***SDSC****.* *Contributors:* In this task the SDSC will merge the work done in T1.1 and T1.2 into reproducible and replicable data knowledge graphs

**Task** **T1.5:** **Visualize** **(M15-M21)** *Leader:* ***SME****.* *Contributors:* In this task the partner SME will apply visualization algorithms to the work done in T1.1 and T1.2 Charles and Miguel: Keep elaborating

**Task** **T1.6:** **All** **participants** **apply** **results** **from** **evolutionary** **semantic** **algorithms** **and** **multilayer** **network** **metrics** **into** **a** **fully** **automated,** **reproducible** **and** **animated** **sustain-ability** **exploitation** **of** **the** **Seas** **case** **study** **(M15-M24)** *Leader:* ***EBD-CSIC****.* *Contributors:* *1,2,3,4,5*

Evolutionary semantic algorithms and multilayer network metrics will search and transform many source-data (i.e., Fishery data using the [(global ﬁshing watch)](https://globalfishingwatch.org/), species interactions, environemental data and social and stakeholders groups with diﬀerent interests within each of the countries, etc, together with the sustain-ability of the Seas database started in 1965 contains around 9 million entries, 1612 species, 20 countries and 11 sampling methods (Figure 2).

**Deliverables**

**D1.1** Software evolutionary semantic rules for data discovery **(M18)**

**D1.2** Report on deﬁnition of multilayer network metrics applied to data discovery **(M18)** **D1.3** Automated demonstrator of evolutionary semantic rules for data discovery **(M21)** **D1.4** Reproducible demonstrator of evolutionary semantic rules for data discovery **(M21)**

**~~D1.5~~** ~~Visualization demonstrator of evolutionary semantic rules for data discovery~~ **~~(M21)~~**

ROBHOOT 14 May 26, 2020

3.1. Research methodology and work plan, work packages and deliverables

**D1.6** Demonstrator all parts for the sustainability exploitation of the Seas case study **(M24)**

**Work** **package** **number** **2** **Lead** **beneﬁciary** **TARTU** **Work** **package** **title** **Causal** **knowledge** **discovery**

**Participant** **number**

**Short** **name** **of** **participant** **Person** **month** **per** **participant** **Start** **month**

**End** **month**

6 7 EAWAG

9 (Provisional) 7

30

TARTU

6 (Provisional)

**Objectives**

• Develop a evolutionary-biology-AI inspired framework for causality discovery • Derive functionality rules required for causality-based computation discovery

• Adaptive learning rules to mimic the empirical patterns for sustainability of the Seas

**Description** **of** **work**

**Task** **T2.1:** **Develop** **eco-evolutionary** **dynamics** **modeling** **...** **(M7-M24)** *Leader:* ***EAWAG****.* *Contributors:* *6*

... T2.1 providescomputation algorithmswith evolving traitsand interactionsto allow WP2 toimplement this feature in causal knowledge discovery. This is particularly relevant in Earth, Ecosystem and Sustainability science. The rapid progress of AI as an automated and explainable technology ([10, 15, 17, 19, 25, 26],+++) will increase our ability to make stronger inferences about future sustainability challenges and solutions [27]. Yet, eco-evolutionary biology-AI-inspired computation discovery solutions will be required to explore a broader range of scenarios with changing functions and .... Carlos:Keep elaborating

**Task** **T2.2:** **This** **task** **extends** **T2.1** **into** **evolutionary** **biology-inspired** **deep** **learning** **networks** **metrics** **for** **general** **principles** **of** **causal** **discovery** **(M7-M24)** *Leader:* ***TARTU****.* *Contributors:* *8*

Raul:Keep elaborating

**Task** **T2.3:** **Based** **on** **the** **framework** **developed** **in** **T2.1** **and** **T2.2,** **ICREA** **will** **derive** **automation** **rules** **for** **data** **discovery** **(M21-M27)** *Leader:* ***ICREA****.* *Contributors:* *3* Automation rules [19] for evolutionary semantic algorithms and multilayer network metrics search and rules transformation for data discovery.Roger:Keep elaborating

**Task** **T2.4:** **Reproduce** **(M21-M27)** *Leader:* ***SDSC****.* *Contributors:* *4* In this task the SDSC will merge the work done in T2.1 and T2.2 into reproducible data knowledge graphs Christine:Keep elaborating

**Task** **T2.5:** **Visualize** **(M21-M27)** *Leader:* ***SME****.* *Contributors:* *5* In thisitask the partner SME will apply visualization algorithms to the work done in T2.1 and T2.2 Charles

**Task** **T2.6:** **All** **participants** **apply** **results** **from** **eco-evolutionary** **AI** **algorithms** **and** **deep** **learning** **networks** **into** **a** **fully** **automated,** **reproducible** **and** **animated** **sustainabil-ity** **of** **the** **Seas** **case** **study** **(M21-M30)** *Leader:* ***EAWAG****.* *Contributors:* *6,7,8,3,4,5*

0.05 in **Deliverables**

**D2.1** Report on deﬁnition of eco-evolutionary biology-AI-inspired rules for causal discovery **(M18)**

**D2.2** Report on deﬁnition of eco-evolutionary process-based deep learning networks applied to causal computation discovery **(M18)**

**D2.3** Automated demonstrator of eco-evolutionary biology-AI-inspired rules for causal discovery **(M21)**

**D2.4** Reproducible demonstrator of eco-evolutionary biology-AI-inspired rules for causal discovery **(M21)**

**D2.5** Visualization demonstrator of evolutionary semantic rules for data discovery **(M21)** **D2.6** Demonstrator all parts for the sustainability exploitation of the Seas case study **(M24)**

ROBHOOT 15 May 26, 2020

3. Implementation

|  |  |
| --- | --- |
| **Work** **package** **number** **3** **Lead** **beneﬁciary** **UNIGRAZ** | |
| **Work** **package** **title** | **Discovery** **in** **federated** **networks** |
| **Participant** **number** | 8 9 |
| **Short** **name** **of** **participant** | SRC UNIGRAZ |
| **Person** **month** **per** **participant** | X X |
| **Start** **month** **End** **month** | 13 36 |

**Objectives**

• Develop a evolutionary-biology inspired framework for discovery in federated networks • Derive functionality rules required for computation discovery in federated networks

• Adaptive learning rules to discover novel paths for sustainability of the Seas

**Description** **of** **work**

**Task** **T3.1:** **Develop** **eco-evolutionary** **biology-inspired** **modeling** **for** **discovery** **in** **feder-ated** **networks** **(M13-M36)** *Leader:* ***SRC****.* *Contributors:* *10* This task extends eco-evolutionary biology-inspired modeling for general principles of discovery in federated networks... Jon:Keep elaborating

**Task** **T3.2:** **Develop** **evolutionary** **neurobiology-inspired** **algorithms...** **(M13-M36)** *Leader:* ***UNIGRAZ****.* *Contributors:* *9*

... T3.2 provides computation algorithms with evolving neurons with (many) traits and interactions to allow WP3 to implement this feature in discovery in federated networks.... Wolfgang:Keep elaborating

**Task** **T3.3:** **Based** **on** **the** **framework** **developed** **in** **T3.1** **and** **T3.2,** **ICREA** **will** **derive** **automation** **rules** **for** **discovery** **in** **federated** **networks** **(M25-M36)** *Leader:* ***ICREA****.* *Contributors:* *3*

Automation rules for eco-evolutionary and neurobiology-inspired modeling for discovery in federated networks Roger:Keep elaborating

**Task** **T3.4:** **Reproduce** **(M21-M27)** *Leader:* ***SDSC****.* *Contributors:* *4* In this task the SDSC will merge the work done in T3.1 and T3.2 into reproducible and replicable discovery in federated networksChristine:Keep elaborating

**Task** **T3.5:** **Visualize** **(M21-M27)** *Leader:* ***SME****.* *Contributors:* *5* In this task the partner SME will apply visualization algorithms to the work done in T3.1 and T3.2Charles:Keep elaborating

**Task** **T3.6:** **Sustainability** **of** **the** **Seas** **federated** **network** **(M21-M30)** *Leader:* ***UNIGRAZ****.* *Contributors:* *6,7,8,9,10*

All participants apply results from eco-evolutionary and neurobiology-inspired algorithms into a fully auto-mated, reproducible and animated sustainability of the Seas federated network case study

**Deliverables**

**D3.1** Demonstrator on eco-evolutionary biology-inspired rules for discovery in federated networks **(M30)** **D3.2** Demonstrator on evolutionary neurobiology-inspired rules for discovery in federated networks **(M36)** **D3.3** Automated demonstrator of for evolutionary biology-inspired rules in federated networks **(M36)** **D3.4** Reproducible demonstrator of evolutionary rules in federated networks **(M36)**

**D3.5** Visualization demonstrator of evolutionary rules for discovery in federated networks **(M36)** **D3.6** Demonstrator all parts for the sustainability of the Seas federated network case study **(M36)**

|  |  |
| --- | --- |
| **Work** **package** **number** **4** **Lead** **beneﬁciary** **IEO** | |
| **Work** **package** **title** | **Dissemination** |
| **Participant** **number** | 10 11 |
| **Short** **name** **of** **participant** | IEO SEM |
| **Person** **month** **per** **participant** | X X |
| **Start** **month** **End** **month** | 1 36 |

ROBHOOT 16 May 26, 2020

3.1. Research methodology and work plan, work packages and deliverables

|  |
| --- |
| **Objectives**  • This WP deals with the system entire scope of dissemination of results in the research community and for the general public. Connection to SME for visualization |
| **Description** **of** **work**  **Task** **T4.1:** **Paco:Keep** **elaborating...** **(M7-M24)** *Leader:* ***IEO****.* *Contributors:* *10*  **Task** **T4.2:** **Paco:Keep** **elaborating** **(M7-M24)** *Leader:* ***IEO****.* *Contributors:* *10*  **Task** **T4.3:** **Paco:Keep** **elaborating** **(M21-M27)** *Leader:* ***IEO****.* *Contributors:* *10*  **Task** **T4.4:** **Miguel:Keep** **elaborating** **(M21-M27)** *Leader:* ***SME****.* *Contributors:* *11*  **Task** **T4.5:** **Miguel:Keep** **elaborating** **(M21-M27)** *Leader:* ***SME****.* *Contributors:* *11*  **Task** **T4.6:** **Miguel:Keep** **elaborating** **(M21-M30)** *Leader:* ***SME****.* *Contributors:* *11* |
| **Deliverables** **D4.1** **(M18)** **D4.2** **(M18)** **D4.3** **(M21)** **D4.4** **(M21)** **D4.5** **(M21)** **D4.6** **(M24)** |

|  |  |
| --- | --- |
| **Work** **package** **number** **5** **Lead** **beneﬁciary** **EAWAG** | |
| **Work** **package** **title** | **Management** |
| **Participant** **number** | 2 6 |
| **Short** **name** **of** **participant** | EAWAG IFISC-CSIC |
| **Person** **month** **per** **participant** | 6 6 |
| **Start** **month** **End** **month** | 7 30 |
| **Objectives**  • Management and work process of the project during the contractual period. • Administrative and ﬁnancial management of the project.  • Ensure the delivery of the project on time and on budget.  • Co-ordinate the technological and scientiﬁc orientation of the project.  • Secure the quality of the work and of the delivered documents and softwar | |
| **Description** **of** **work**  **Task** **T5.1:** **Carlos:Keep** **elaborating** **(M1-M36)** *Leader:* ***EAWAG****.* *Contributors:* *8*  **Task** **T5.2:** **Victor:Keep** **elaborating** **(M36-M27)** *Leader:* ***IFISC-CSIC****.* *Contributors:* *1* | |

Table 3.1c: Deliverable list

ROBHOOT 17 May 26, 2020

3. Implementation

Table 3.1b: Deliverable list

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Delive-rable** **num-ber** | **Deliverable** **name** | **WP** **no.** | **Lead** **partic-ipant** **name** | **Na-tu-re** | **Disse-mina-tion** **Level** | **Delivery** **date** **(proj.** **month)** |
| **D1.1** | Software evolutionary semantic rules for data discovery | WP1 | EBD-CSIC | R | PU | 18 |
| **D1.2** | Report on deﬁnition of multilayer network metrics applied to data discovery | WP1 | IFICS-CSIC | R | PU | 18 |
| **D2.1** | Report on deﬁnition of eco-evolutionary biology-AI-inspired rules for causal discov-ery | WP2 | EAWAG | R | PU | 18 |
| **D2.2** | Report on deﬁnition of eco-evolutionary process-based deep learning networks ap-plied to causal computation discovery | WP2 | TARTU | R | PU | 18 |
| **D4.1** |  | WP4 | IEO | R | PU | 18 |
| **D4.2** |  | WP4 | IEO | R | PU | 18 |
| **D1.3** | Automated demonstrator of evolutionary se-mantic rules for data discovery | WP1 | ICREA | D | PU | 21 |
| **D1.4** | Reproducible demonstrator of evolutionary semantic rules for data discovery | WP1 | SDSC | R | PU | 21 |
| **D1.5** | Visualization demonstrator of evolutionary semantic rules for data discovery | WP1 | SME | R | PU | 21 |
| **D2.3** | Automated demonstrator of eco-evolutionary biology-AI-inspired rules for causal discovery | WP2 | ICREA | D | PU | 21 |
| **D2.4** | Reproducible demonstrator of eco-evolutionary biology-AI-inspired rules for causal discovery | WP2 | SDSC | R | PU | 21 |
| **D2.5** | Visualization demonstrator of evolutionary semantic rules for data discovery | WP2 | SME | R | PU | 21 |
| **D4.3** |  | WP4 | SME | D | PU | 21 |
| **D4.4** |  | WP4 | SME | R | PU | 21 |
| **D4.5** |  | WP4 | SME | R | PU | 21 |
| **D1.6** | Demonstrator all parts for the sustainability exploitation of the Seas case study | WP1 | EBD-CSIC | R | PU | 24 |
| **D2.6** | Demonstrator all parts for the sustainability exploitation of the Seas case study | WP2 | EAWAG | R | PU | 24 |
| **D4.6** |  | WP4 | SME | R | PU | 24 |
| **D3.1** | Demonstrator on eco-evolutionary biology-inspired rules for discovery in federated net-works | WP3 | SRC | D | PU | 30 |
| **D3.2** | Demonstrator on evolutionary neurobiology-inspired rules for discovery in federated net-works | WP3 | UNIGRAZ | D | PU | 36 |
| **D3.3** | Automated demonstrator of for evolution-ary biology-inspired rules in federated net-works | WP3 | ICREA | D | PU | 36 |
| Continued on next page | | | | | |  |

ROBHOOT 18 May 26, 2020

3.2. Management structure, milestones and procedures

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **D3.4** | Reproducible demonstrator of evolutionary rules in federated networks | WP3 | SDSC | D | PU | 36 |
| **D3.5** | Visualization demonstrator of evolutionary rules for discovery in federated networks | WP3 | SME | D | PU | 36 |
| **D3.6** | Demonstrator all parts for the sustainability of the Seas federated network case study | WP3 | UNIGRAZ | D | PU | 36 |

**Table** **3.2a:** **List** **of** **milestones**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Milestone number | Milestone name | Related work package(s) | Due data (months) | Veriﬁcation |
| M1 | Data knowl-edge discovery | WP1 | 28 | OS-Software,Paper/Conf.,Main-website |
| M2 | Causal knowl-edge discovery | WP2 | 30 | OS-Software,Paper/Conf.,Main-website |
| M3 | Discovery  in federated networks | WP3 | 36 | OS-Software,Paper/Conf.,Main-website |

**3.2** **Management** **structure,** **milestones** **and** **procedures**

**Management** **procedures** **and** **structure**:

All partners of ROBHOOT are organized by the Project Manager, with a Steering Board (SB) and an external Scientiﬁc Advisory Committee (SAC). The SB, which will consist of one representative from each partner and the Project Manager, will meet at least once a year. The SB will have the overall responsibility for the technical, ﬁnancial, administrative, legal, dissemination aspects of the project, and risk analysis. The SAC, headed by the Coordinator, will consist of senior experts in the respective ﬁelds: Prof. Elisa Thebault, France (expert in theoretical ecology and ecological networks), Mercedes Pascual, USA (expert in complex system modeling, to be conﬁrmed), and Catherine Graham, Switzer-land (expert in biogeography and ecological netowrks, to be conﬁrmed)... have agreed to be members of the SAC.

**Management** **activities**:

The project coordinator (CJ Melian, EAWAG) will coordinate the work and its scientiﬁc input, com-municate with EC, and organize the project reviews with the EC. The Project Manager (To be named) will work on administrative, ﬁnancial and dissemination activities, and risk management. Mention the IPR team... to set-up regulated by a Consortium Agreement. WP leaders will be responsible for WP planning, scientiﬁc and WP activities. WP groups will meet for the speciﬁc needs of each WP. **Methods** **for** **monitoring** **and** **reporting** **progress**:

Meeting and reporting schedule is planned as: Every 3 months (oral and video-conferences) WP leaders report to the coordinator. Every 6 months the coordinator summarizes overall status to the SB. Every 6 to 12 months the coordinator setups SB meeting to review the progress of the project and to critically review the outlook for eﬀective communication and deliverables. At months 12, 24 and 36 the SB pre-pares consolidated management and annual activity reports and also the coordinator and the Project Manager setup SAC meetings to obtain advice and feedback. **Keep** **elaborating** **about** **newcomers,** **gender** **balance,** **previous** **collaborations**

**Table** **3.2b:** **Critical** **risks** **for** **implementation**

ROBHOOT 19 May 26, 2020

3. Implementation

(TO BE DONE)

|  |  |  |
| --- | --- | --- |
| **Description** **of** **risk** | **WP** | **Proposed** **risk-** **mitigation** **mea-sures** |
| Evolutionary semantic algorithms insuﬃciently developed: Medium | WP1 | Consider more developed genetic programming methods to infer data interactions. |
| Multilayer metrics accounting for spatiotemporal patterns along many datasets insuﬃciently developed: Low | WP1 | Implementation of more standard complex networks metrics to charac-terize data knowledge discovery. |
| Low number of training data avail-able: Medium | WP2 | Alternative methods focusing on ma-trix decomposition methods. |
| Automated evolutionary-inspired expressions for causal knowledge discovery insuﬃciently developed: Medium | WP2 | Symbolic regression methods to full automation for causal discovery ac-counting for evolutionary rules. |
| Eco-evolutionary dynamics of multi-ple traits in species-rich ecosystems insuﬃciently developed: Medium | WP3 | Mean-ﬁeld approximations using classicalODEsystemsandnoveluni-versal diﬀerential equations for sci-entiﬁc machine learning. |
| Evolutionary neurobiology-inspired federated networks insuﬃciently de-veloped: Medium | WP3 | Spiking neural network models as alternatives to evolutionary neural biology-inspired algorithms in feder-ated networks. |
| Cooperative forecasting mixing eco-evolutionary dynamics and neu-ral nets in large scale federated networks insuﬃciently developed: Medium | WP3 | Mix eco-evolutionary dynamics models with less alternative neural nets models working a smaller spatiotemporal scales. |

**3.3** **Consortium** **as** **a** **whole**

ROBHOOT is a science-enabled multi-feature technology designed with a highly modular structure. Modularity allows to gain module functionality while maintaining cross-functional features among the diﬀerent parts to produce a science-enabled interdisciplinary technology (Figure 1, WP one to three and milestones one to three, red, green and blue, respectively): Data knowledge discovery’s team requires skills in evolutionary biology, evolutionary computation, computer science and the physics of complex systems (Section 3.1.1, Table 3.2a). ROBHOOT v.1.0 work mixes expertise in seman-tic algorithms, evolutionary computation algorithms and multilayer network metrics to create novel evolutionary-biology inspired ontology annotations along heterogeneous data-sources into one data knowledge discovery. EBD-CSIC team takes care of data knowledge graphs introducing novel evo-lutionary semantic algorithms to decipher ontologies and interactions among many data-sources ( D1.1, Tables 3.1a-c). IFISC-CSIC team focuses on multilayer network modularity, community detection and decentralization metrics for pattern detection in data knowledge discovery (D1.2, Tables 3.1a-c). All teams in WP1 will join eﬀorts to merge evolutionary semantic algorithms, multilayer network metrics, automation, reproducibility and visualization to produce the data knowledge discovery graph for the sustainability of the Seas case study (D1.6, Tables 3.1a-c). ROBHOOT v.2.0’s team composed by EAWAG, and TARTU ULIKOOL and will merge eco-evolutionary biology-inspired networks to deep

ROBHOOT 20 May 26, 2020

3.3. Consortium as a whole

learning networks, the “Evolutionary biology-inspired AI algorithms” approach (D2.1 and D2.2, Box 1, Table 3.1a-c and Figure 1, green). The overall goal of this milestone is to connect evolutionary biology mechanisms to deep learning networks to generate a causal knowledge discovery technology to make patterns interpretable (Deliverable D2.2, Section 3.1.2, Table 3.2.a-c and Figure 3). The team for this milestone add inter-module complementarity expertise to ROBHOOT v.1.0’s team: Now the skills focus on data-scientists trained in deep learning networks and evolutionary biologists with expertise in evolutionary ecology theory and evolutionary-inspired networks (section 3.1.2 and Figure 1, green). Milestone two generates a causal knowledge discovery for the sustainability of the Seas containing 9 mil-lion entries, 1612 species using around 11 sampling methods and more than 15 countries (D2.6, Figures 1, green). Interdisciplinarity in ROBHOOT is achieved not only at the intra-module development stage, but also at the inter-module stage where causal knowledge discovery and evolutionary biology-inspired AI algorithms might form the basis for the interdisciplinarity breakthrough ideas reﬂected in the highly complementarity skills of the consortium. The ﬁrst two modules in ROBHOOT contain researchers from Estonia, Spain and Switzerland.

The ROBHOOT consortium wants to advance the rapidly evolving digital ecosystem by making co-operative discovery a fundamental feature of it. For this purpose, a science-enabled data and causal knowledge discovery technology is not enough if they stay isolated from a discovery technology em-bedded in large-scale networks. To discover novel scenarios for ecosystem sustainability, Discovery in federated networks should learn to learn from heterogeneous data-sources in the context of evolution-ary neural biology-inspired algorithms. To achieve scalability for the discovery in federated networks, eco-evolutionary dyamics and neural-inspired protocols in federated networks is the excellency fea-ture of ROBHOOT v.3.0 (section 3.1.3). ROBHOOT v.3.0’s team composed by SRC and UNIGRAZ, develop eco-evolutionary dynamics scenarios for ecosystem sustainability and neural biology-inspired federated networks, respectively (Box 2). The team forming ROBHOOT v.3.0 also requires contrast-ing skills: First, theoreticians working in eco-evolutionary dynamics guarantee scalable implementation of evolutionary processes in federated networks. Second, neurobiologists in collaboration to developers aiming to explore the role of evolving neural biology-inspired solutions accounting for heterogeneity and dimensionality in federated networks. ROBHOOT v.3.0 is a fundamental stepping-stone for develop-ing “Cooperative Forecasting”: it ﬁrst guarantees proper eco-evolutionary dynamics along species-rich ecosystems is implemented. Then these species-rich ecosystems represent the basis for discovery of novel paths that increase sustainability goals. And these novel paths are searched along many nodes of a network replicating eco-evolutionary dynamics scenarios that interact and learn from each other to ﬁnd better forecasting scenarios at a global scale. ROBHOOT v.3.0’s implements heterogeneous groups of cooperating and competing neurons in federated networks for making cooperative forecasting a standard global property of ROBHOOT (Deliverable D3.2, Tables 3.1a-c). Milestone three generates discovery in federated networks for the sustainability of the Seas to provide populations of scenarios satisfying biodiversity and sustainability maintenance while guaranteeing commercial interest of many interacting groups and stakeholders within and among countries (Deliverable D3.6, Figure 3, blue). ROBHOOT v.3.0 contain researchers from Sweden and Austria. ROBHOOT architecture aims to guar-antee strong reproducibility, automation, and visualization-communication along its whole life cycle and development. The team formed by the SDSC (D1.4, D2.4 and 3.4), ICREA (D1.3, d2.3 and D3.3, and SME (D2.5, D3.5 and D4.5), will implement reproducibility, automation, and visualization and reporting, respectively, features crossing all ROBHOOT milestones to secure dissemination along its life cycle (Figure 1 and Gantt chart).

ROBHOOT 21 May 26, 2020

Bibliography

**3.4** **Resources** **to** **be** **committed**

**Bibliography**

[1]

[2] *Blue-cloud*.

[3] *Elixir* *open* *data*.

[4] *HOT*.

[5] *Knowledge* *Graph* *COVID-19*.

[6] *Openstreet*.

[7] Elli Androulaki, Artem Barger, Vita Bortnikov, Srinivasan Muralidharan, Christian Cachin, Konstantinos Christidis, Angelo De Caro, David Enyeart, Chet Murthy, Christopher Ferris, Gennady Laventman, Yacov Manevich, Binh Nguyen, Manish Sethi, Gari Singh, Keith Smith, Alessandro Sorniotti, Chrysoula Stathakopoulou, Marko Vukoli´c, Sharon Weed Cocco, and Jason Yellick. Hyperledger Fabric: A Distributed Operating System for Permissioned Blockchains. *Proceedings* *of* *the* *13th* *EuroSys* *Conference,* *EuroSys* *2018*, 2018-Janua, 2018.

[8] BigchainDB GmbH. BigchainDB: The blockchain database. *BigchainDB.* *The* *blockchain* *database.*, (May):1–14, 2018.

[9] Emanuele Cozzo and Yamir Moreno. Dimensionality reduction and spectral properties of multilayer networks. 2018.

[10] Kyle Cranmer, Johann Brehmer, and Gilles Louppe. The frontier of simulation-based inference. pages 1–10, 2019.

[11] Manlio De Domenico, Albert Sol´e-Ribalta, Elisa Omodei, Sergio G´omez, and Alex Arenas. Ranking in interconnected multilayer networks reveals versatile nodes. *Nature* *Communications*, 6:1–6, 2015.

[12] Johnny Dilley, Andrew Poelstra, Jonathan Wilkins, Marta Piekarska, Ben Gorlick, and Mark Friedenbach. Strong Federations: An Interoperable Blockchain Solution to Centralized Third-Party Risks. 2016.

[13] Nikolai Durov. Telegram Open Network. pages 1–132, 2017.

[14] Fussmann G. F., Loreau M., and Abrams P. A. Eco-evolutionary dynamics of communities and ecosystems. *Functional* *Ecology*, 21:465–477, 2007.

[15] Giuseppe Futia and Antonio Vetr`o. On the integration of knowledge graphs into deep learning models for a more comprehensible AI-Three challenges for future research. *Information* *(Switzerland)*, 11(2), 2020.

[16] Hairston N. G., Ellner S. P., Geber M. A., Yoshida T., and Fox J. A. Rapid evolution and the convergence of ecological and evolutionary time. *Ecology* *Letters*, 8:1114–1127, 2005.

[17] Yolanda Gil and Bart Selman. A 20-Year Community Roadmap for Artiﬁcial Intelligence Research in the US. aug 2019.

[18] Golem. The Golem Project Crowdfunding Whitepaper. *Golem.Network*, (November):1–28, 2016.

[19] Roger Guimera`, Ignasi Reichardt, Antoni Aguilar-Mogas, Francesco A. Massucci, Manuel Miranda, Jordi Pallar`es, and Marta Sales-Pardo. A Bayesian machine scientist to aid in the solution of challenging scientiﬁc problems. *Science* *Advances*, 6(5):eaav6971, 2020.

[20] Vlad Gu¨nther and Alexandru Chirita. ” Scienceroot ” Whitepaper. 2018.

[21] Raban Iten, Tony Metger, Henrik Wilming, L´ıdia Del Rio, and Renato Renner. Discovering Physical Concepts with Neural Networks. *Physical* *Review* *Letters*, 124(1):1–18, 2020.

ROBHOOT 22 May 26, 2020

Bibliography

[22] Wolfgang Maass. Noise as a resource for computation and learning in networks of spiking neurons. *Proceedings* *of* *the* *IEEE*, 102(5):860–880, 2014.

[23] Wolfgang Maass. To Spike or Not to Spike: That Is the Question. *Proceedings* *of* *the* *IEEE*, 103(12):2219–2224, 2015.

[24] Ocean Protocol Foundation, BigchainDB GmbH, and DEX Pte. Ltd. Ocean Protocol: A Decentralized Substrate for AI Data & Services Technical Whitepaper. pages 1–51, 2018.

[25] Anthony O’Hare. Inference in High-Dimensional Parameter Space. *Journal* *of* *Computational* *Biology*, 22(11):997– 1004, 2015.

[26] Esteban Real, Chen Liang, David R. So, and Quoc V. Le. AutoML-Zero: Evolving Machine Learning Algorithms From Scratch. 2020.

[27] Markus Reichstein, Gustau Camps-Valls, Bjorn Stevens, Martin Jung, Joachim Denzler, Nuno Carvalhais, and & Prab-hat. Deep learning and process understanding for data-driven Earth system science. *Nature*.

[28] Ju¨rgen Schmidhuber. Deep learning in neural networks: An overview. *Neural* *Networks*, 61:85–117, jan 2015.

[29] Christian Steinruecken, Emma Smith, David Janz, James Lloyd, and Zoubin Ghahramani. The Automatic Statistician. pages 161–173. 2019.

ROBHOOT 23 May 26, 2020

4. Members of the consortium

**4** **Members** **of** **the** **consortium**

**4.1** **Participants** **(applicants)**

**EAWAG**

Dr. Carlos J. Melian will work for EAWAG in ROBHOOT.

Carlos J Melian takes the oﬃcial coordinator lead of the ROBHOOT project and takes care of all management aspect.

The Swiss Federal Institute for Aquatic Science and Technology (EAWAG) is an independent re-search institute within the Swiss Federal Institute of Technology (ETH) domain. As such it is an independent partner in a network of exceptionally strong research and education institutions (2 fed-eral universities and 4 federal research institutes). EAWAG is world-leading water research institute. EAWAG hosts over 300 research fellows, postdocs and PhD students, who are supported by technical and support staﬀ.

Contributions to ROBHOOT ...

Dr. Carlos Melia´n is a tenured researcher in Theoretical Evolutionary Ecology at EAWAG andassoci-ate professor at the University of Bern. Dr. Melia´n is widely recognized as an expert in Eco-evolutionary networks where he has contributed with novel approaches combining stochastic modeling and empirical patterns to study the interaction between ecological and evolutionary dynamics in multispecies assem-blages. Dr. Melian has made important contributions to the ﬁelds of Ecological Networks (e.g. De Laender and Melia´n, 2014, Ecol Lett; Melia´n and Kˇrivan, 2015, AmNat), Eco-evolutionary networks (e.g. Melia´n et al., 2011, Adv Ecol Res; Andreazzi and Melia´n, 2018, PRSB), and Diversiﬁcation on eco-evolutionary networks (e.g. Melia´n et al., 2012, PLoS Comput Biol; Leprieur, Melia´n, Pellissier, 2016, Nat Commun). Most of his contributions combine stochastic modeling, large empirical datasets, and Bayesian approximations, to quantify the impact of intra- and inter-speciﬁc trait variation on species interactions, divergence and the macroscopic properties of ecological networks. He has been Principal Investigator in 15 projects obtained in 5 diﬀerent countries (Spain, USA, UK, Germany and Switzer-land) with a total of approx. 1 Million Euro. He has successfully co- supervised 5 PhD students and supervised 7 postdocs. The feasibility of this proposal is ﬁrmly established by his track record further reinforced by his solid and active international network of collaborators. Among others he works with Prof. S. Allesina (U Chicago, USA), Dr. A. Ekl¨of (Linko¨ping U, Sweden), Prof. P. Guimares (U Sao Paulo, Brazil), Prof. M. O’Connor (U Vancouver, Canada), and Dr. F. De Laender (U Namur, Belgium). Dr. Melia´n has expertise combining skills in networks and experienced in modelling complex multi-scale eco-evolutionary networks. He also has combined basic and applied-oriented research; 2) Integrating a range of methodologies: he is experienced with statistical and mathematical modelling, and has analytical and advanced programming skills; 3) Extensive experience collaborating with theo-rists and empiricists: he has collaborated with researchers of diverse ﬁelds i.e. mathematics, ecology, evolutionary biology, conservation science.

**List** **of** **publications**

• Melia´n C, et al. 2018. Deciphering the interdependence between ecological and evolutionary networks. Trends in ecology evolution 33,7: 504-512.

• Andreazzi C, Guimaraes P, Melia´n C. 2018. Eco-evolutionary feedbacks promote ﬂuctuating selection

ROBHOOT 24 May 26, 2020

4.2. Third parties involved in the project (third party resources)

and long-term stability of antagonistic networks. Proc. R. Soc. B 285: 20172596.

• Meli´an C, Seehausen O, Eguiluz V, Fortuna M, Deiner K. 2015. Diversiﬁcation and Biodiversity Dynamics of Hot and Cold Spots. Ecography 38, 393-401.

• Melia´n C, et al. 2015. Dispersal dynamics in food webs. American Naturalist 185, 2: 157-168.

• Melia´n C., et al. 2014. Individual trait variation and diversity in food webs. Advances in Ecological Research. Vol. 50. Academic Press, 207-241.

**List** **of** **relevant** **projects**

2020 Melia´n, C. J. and Ferra˜o Filho, Aloysio S. Granted: Brazilian-Swiss Joint Research Programme SNSF, Title: Feedbacks between coevolving predator-prey interactions and the funcitoning of aquatic ecosystems. Period: 24 Months, SFr 228k

2018 Melia´n, C. J., Andreazzi, C., and Astegiano, J. SNSF, Scientiﬁc exchange program, Title: Biodi-versity Dynamics in Coevolutionary Metaecosystems. Period: 3 Months, SFr 20k

2016 Melia´n, C. J., Matthews, B., Seehausen, O., and Harmon, L. J. Granted: Swiss National Science Foundation, International exploratory workshops. Title: Interactions on Trees. Period: 1 Week, SFr 21k.

2015 Kalinkat, G., and Melia´n, C. J. Granted: German Academic Exchange Service (DAAD). Germany. Title: Analysing the interplay between allometric constraints and intraspeciﬁc trait variation to predict food web dynamics. Period: 6 Months, SFr 19k.

2015 Meli´an, C. J. Granted: Swiss National Science Foundation, Division III. Switzerland. Title: A theory for next- generation food web data. Period: 2 years (Postdoc), SFr 161k.

**Infrastructure** **relevant** **to** **the** **proposed** **work**

EAWAG in Kastanienbaum Lucerne oﬀers excellent oﬃce, meeting rooms, laboratory and testing facil-ities in modern, state-of-the-art buildings. EAWAG provides access to ﬁrst class research facilities that regularly oﬀer training for the use of equipment, tools and software. Of particular relevance for this research project is the access to two computing clusters “Leonhard” and “Euler” with more than 50 000 processor cores available for scientiﬁc computations, and training for their use oﬀered by ETH Zu¨rich.

**4.2** **Third** **parties** **involved** **in** **the** **project** **(third** **party** **resources)**

**5** **Ethics** **and** **Security**

**5.1** **Ethics**

**5.2** **Security**

1

1Article 37.1 of the Model Grant Agreement: Before disclosing results of activities raising security issues to a third party (including aﬃliated entities), a beneﬁciary must inform the coordinator – which must request written approval from the Commission/Agency. Article 37.2: Activities related to “classiﬁed deliverables” must comply with the “security requirements” until they are declassiﬁed. Action tasks related to classiﬁed deliverables may not be subcontracted without prior explicit written approval from the Commission/Agency. The beneﬁciaries must inform the coordinator – which must immediately inform the Commission/Agency – of any changes in the security context and –if necessary – request for Annex

ROBHOOT 25 May 26, 2020

5. Ethics and Security

1 to be amended (see Article 55).

ROBHOOT 26 May 26, 2020

5.2. Security

ROBHOOT 27 May 26, 2020