



# AI Competitions and Benchmarks, Practical issues: Proposals, grant money, sponsors, prizes, dissemination, publicity

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## Chapter 1

# Practical issues: Proposals, grant money, sponsors, prizes, dissemination, publicity

Magali Richard, Yuna Blum, Justin Guinney, Gustavo Stolovitzky, and Adrien Pavão

**Abstract** Each organization of competitions and benchmarks involves a large number of practical problems, such as obtaining sufficient financial support or recruiting participants through appropriate incentives and community engagement. In addition to defining scientific tasks, preparing data and creating challenges, a very important practical administrative organization remains to be achieved. Indeed, cost assessment, corresponding requests for financial support and adequate publicity are key factors for successful organization of the competition. In addition, a good understanding of the incentives that lead participants to engage in a given challenge is fundamental for effective practical organization success. In this chapter, we will cover these topics and give some practical tips and examples for overcoming the “challenge” of organizing the challenges.

**Key words:** communication, proposal, sponsors, practical issues



Fig. 1.1: The incentives for participating in a challenge.

## 1.1 Incentivizing participation

How to incentivize participants to work on complex problems is a key feature of challenge organization. In this section, we review various types of motivations (Figure 1.1), from a participant perspective, and give practical tips to optimize those incentives.

### 1.1.1 Skills : Knowledge acquisition, communication, education

Traditional university programs in Artificial Intelligence are evolving rapidly, trying to meet the new needs of students, especially on their ability to work collaboratively while improving their scientific knowledge on data mining. Data challenges

are mainly based on a cooperative model, which has the advantage of responding to this dual motivation. Coopetition [1] is an active learning pedagogical approach based on the combination of a strategy of competition, where students compete for the best result, and cooperation, where students collaborate for a mutual benefit. Coopetition-based data challenges have the advantage of simultaneously offering two types of learning. On the one hand, this gives a participant a solid methodological training on the scientific question addressed, thanks to the sharing of knowledge between professors and students, but also between the students themselves. On the other hand, these approaches allow students to acquire new skills in collaboration, communication and networking. For more details, please refer to chapter 9: Competitions and challenges in education.

Educational data challenges can be organized into teamwork, recruiting participants from different backgrounds (academic and cultural), with a scientific preparation that can range from minimal information about the challenge before starting to full preparation through a series of dedicated conferences. To meet the expectations of the students, a key factor is the will of the organizer to build a "friendly environment" which will help to boost the motivation of the students and their self-esteem, and to focus more on the process itself than on the results and objectives. Building multidisciplinary teams with different scientific expertise and focusing on real problems are important aspects in the organization of educational challenges. It is also important to provide an environment where participants can communicate with their team members, other teams, and teachers. Setting the right reward and price is a major motivator for winning student buy-in [2].

Finally, organization of competitions itself can be used as a pedagogical tool. Designing such task is complex and can be, in some regards, more interesting than solving it [3].

### ***1.1.2 Hot topics : scientific crowdsourced benchmarking***

The quintessential challenge revolves around an existing quantitative standard or benchmark, and seeks to improve upon state-of-the-art. One of the more longstanding benchmark initiatives is the Critical Assessment for Structural Proteins (CASP), which asks participants to predict protein structure (folding) from protein sequence. Groups who specialize in this domain are naturally incentivized to compare their approach in the structured and objective format of a data challenge in the hope that their method out-competes other approaches and can therefore become a new standard in the field [4]. CASP is now recognized within the protein structure community as the *de facto* forum for assessing algorithms, and is therefore as much an incentive as a mandate for formal recognition with the community. This incentive generalizes to all specialties, including image recognition (e.g. MNIST [5], ImageNet [6]), gene identification and function prediction (e.g. RGASP [7], CAFA [8]) or drug binding (e.g. on going DREAM drug binding challenge).

Any published AI algorithm is expected to include a formal performance comparison against state-of-the-art methods. No good data-driven approach could emerge without good quality, well curated data. This task can be cumbersome and require a great deal of work to assemble and prepare benchmark datasets. Depending on the type of data, data acquisition and/or generation can be very time-consuming and costly (see cost section below). Consequently, a natural perk of a scientific data challenge is that the work involved to generate and prepare a benchmarking dataset is managed by the challenge organizers. Therefore, AI competitions offer a playground with data that are usually costly and complicated to generate. Access to these types of datasets is a strong motivation for participants aiming to develop cutting edge methodological approaches to solve a complex scientific problem.

Recurrent challenges also present the advantage of keeping people on a regular schedule, as they expect the challenge to come and reserve time for it. As for a classic scientific event, it provides participants the opportunity to expand their professional network and to start new collaborations with people working in the same research field or people from different disciplines gravitating around the same topic. Finally, data challenges remain the best functioning way of implementing competitions: people compete and get credit for winning, then they share their solution publicly and the community can move together to the next step.

### ***1.1.3 Environment and awards***

One appealing aspect of the challenges is the spirit of games. This translates into a friendly yet competitive environment along with rewards. It is not unusual to gather common participants on different challenges. An addiction for this type of competition can emerge as well as a thrill of seeing evolution in the social community (particularly true for commercial platforms such as Kaggle). The rewards can be of various nature going from small prizes (e.g. book) to high amounts of money (e.g. 1 million dollars, Salesforce 1 Hackathon) or even positions in companies. Big awards may naturally attract more participants but this has to be balanced against the environment of the challenge and the scientific problem raised.

### ***1.1.4 Visibility, career and recruitment***

Challenges are opportunities for participants to showcase their various skills to recruiters and even get a position at the end. A growing number of organizations are adopting modern hiring practices such as challenges to find best candidates. Recruiters use this tool to assess candidates' technical and behavior skills. Challenges have indeed the great advantage of evaluating many different criteria at the same time. Companies can assess technical competencies such as problem solving skills,

time management and innovations. They can also assess the behavioral skills they value, such as communication, openness to diversity and leadership.

The implementation of a challenge allows recruiters to define certain expectations towards the evaluated candidates (candidates gain insight into the work culture of their future employer), while verifying if their personality corresponds to the company's fundamental values. One of the difficulties in recruitment is that many companies still follow long selection processes that waste time and interest for both candidates and recruiters. To overcome this problem, challenges can be used to evaluate candidates in a short period of time and friendly environment, where they can demonstrate real-time expertise. It can also serve as a pre-selection process that will also save time for recruiters. As a result, such challenges must be carefully designed according to the skills (technical, innovation, leadership ...) one wants to evaluate.

Interestingly, challenges can bring together a larger number of candidates from more diverse backgrounds than traditional recruiting. Organizers can build a portfolio of interesting candidates for present and future positions, without necessarily limiting themselves to the winners of the challenge, especially as winning challenges does not include all skills valuable in project management (such as communication with customers or production standards). For instance, Kaggle, one of the leading challenges platform acting as a recruiting tool, uses a performance tracking system to evaluate participants<sup>1</sup>. Some companies even sell expertise from Kaggle Grandmasters<sup>2</sup>. Besides, challenges are also an excellent way to increase brand awareness. They can be used as a marketing tactic for big companies to reinforce their leadership in their field. Smaller companies can also increase their visibility through challenges and attract more applicants for a position.

Finally, in addition to recruiting new talent, challenges allow companies to bring innovative solutions and ideas to technical problems. Based on the clear success of challenges in the recruitment process, we can easily expect their increase in the upcoming years.

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<sup>1</sup> <https://www.kaggle.com/progression>

<sup>2</sup> <https://h2o.ai/company/team/kaggle-grandmasters/>

### Practical tips and resources to optimize incentivization

- Define your working plan and your objectives<sup>a</sup>
- Carefully prepare benchmarking datasets (see Chapter 3 on data preparation).
- Set up a website to collect a list of interested people<sup>b</sup>.
- Bring together a expert steering committee
- Provide good educational materiel together with the challenge (i.e. a good starting kit, white paper).
- Make yourself available during the challenge to answer questions.
- Be responsive to questions on the forum.
- For a recurrent challenge, provide open-source previous winning solutions.
- Organize good publication venues (see details and examples in section 12.2 Community engagement)
- Associate with established conferences (see details and examples in section 12.2 Community engagement)
- For education challenges, you can find inspiration on existing education challenges on open-source platforms such as RAMP<sup>c</sup>, or Codalab<sup>d</sup>

<sup>a</sup> 10 tips here: <http://www.chalearn.org/tips.html>

<sup>b</sup> see e.g. <https://l2rpn.chalearn.org/>

<sup>c</sup> <https://ramp.studio>

<sup>d</sup> <https://codalab.lisn.upsaclay.fr/>

## 1.2 Community engagement

Mechanisms for engaging and disseminating a competition towards a targeted community are complex and highly dependant on the scientific field. In this section, we try to review general aspects of community engagement that could help challenge organizers to properly define their strategy. See Figure 1.2 and Table 1.1 for a review of community engagement strategies and examples of recent competitions.

### 1.2.1 Organization of the challenge

The community that will engage in a specific competition will depend on several key aspects of defining the challenge. First, the organizers should define an optimal number of participants (which includes the maximum number of participants allowing the challenge to be held properly). Large open competitions have the advantage of ensuring visibility and optimizing scientific production (in the case of

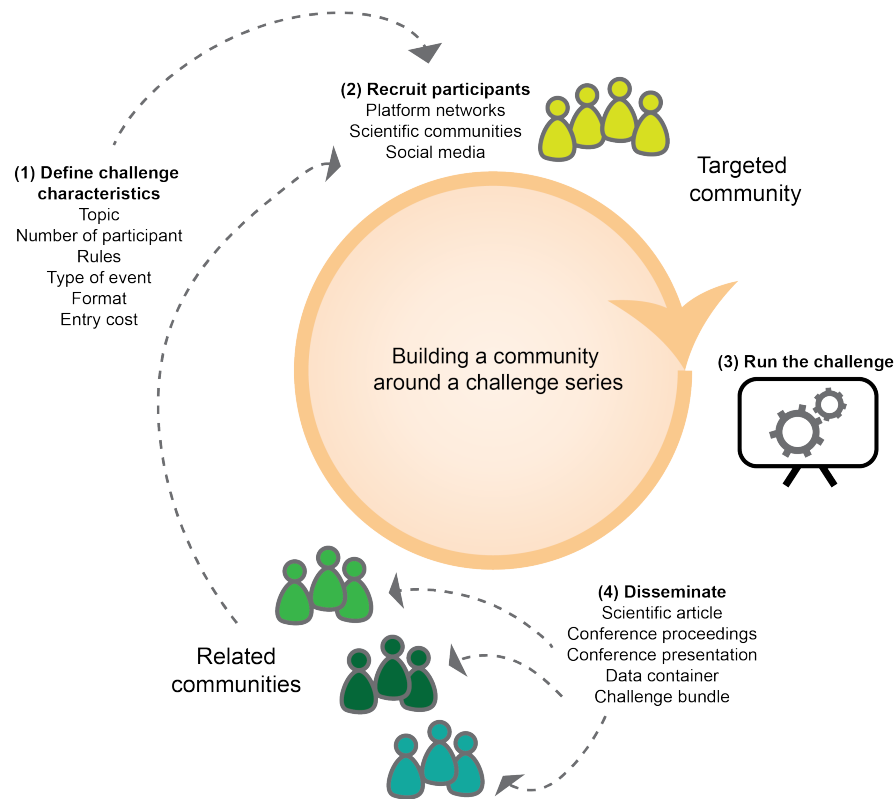


Fig. 1.2: The process of engaging a community

crowdsourced benchmarking for example) while smaller competitions will promote communication between participants (more adapted to challenges aiming at educational results). Interestingly, recent challenges run a pre-selection to avoid crowding the final run, which may be expensive in computational resources. Then they have to determine an entry cost: is it easy to participate in the competition? The entry cost depends on several factors: clarity of the rules, specificity of the tasks, size of the dataset, computational resources required to run the methods... All of this will have an impact on the participants who will enter the competition and indirectly define the target audience. Finally, the organizers should establish what the format of the competition will be: online events will increase the chances of getting a large pool of participants while in-person events (e.g. at dedicated schools or at scientific conferences) are more suitable for collaborative team work. Once all these parameters are specified, organizers can adapt their communication strategy accordingly and start communicating through dedicated channels, such as the scientific communities mailing list, the digital challenge platform networks and the social media.



### ***1.2.2 Challenge output dissemination***

The dissemination of the data challenge can take several formats (complementary and not exhaustive) and should match the following question : how would it serve the targeted community?

Participatory benchmarking competitions generally result in scientific publications (see examples [9, 10, 11, 12, 13, 14]) which will be of use to the community. Offering authorship to competing teams, along with participation in manuscript design and writing, is also a strong incentive that will provide international visibility and recognition to participants. Organizers might try to connect with high-profile journal editors ahead of the challenge organization to discuss the possibility of publishing the competition outcome. Depending on the scientific field of the competition, publications can take various form, such as scientific articles, contributions to special issues, conference proceedings, or even books. Best performing teams can also be offered the ability to present their solution in a international scientific conference (e.g. RECOMB/ISCB for DREAM deconvolution challenge). In addition to an article describing the results of the competition, a challenge built on the data to modeler model [15] could also result in publishing the benchmark dataset along with a container providing a reproducible and continuous benchmark (e.g. a dedicated docker container). Competition data can then be re-used by research scientists as gold standard for new computational methods that will be developed in the future. Challenge organizers may also consider giving open access to their challenge design and templates, especially regarding educational challenges, so that these competition can be massively disseminated to various universities at no cost.

Challenge output and dissemination strategy differ a lot according to the competition organizers and environments. Academic competitions massively rely on the open science framework, encouraging participants to submit their code under an open source license (ex: L2RPN, DREAM challenges). On the opposite, private companies are often motivated by solving an theoretical and methodological obstacle in order to further develop private commercial solutions that will be put on the market. Such organizers may be more inclined to follow a 'private output' model where participant surrender intellectual property of their findings in exchange for earning money prizes.

COMMUNITY ENGAGEMENT					
Name	Field	Year	Platform	Number of participants	Dissemination
TrackML Particle Tracking Challenge	Physics	2018	Kaggle	739 participants	IEEE WCCI competition (Rio de Janeiro, Jul 2018) and NIPS competition (Montreal, Dec 2018)
LAP series	Computer Vision	2013-22	CodaLab	XXX	Springer Series on Challenges in Machine Learning, ECCV, IEEE TPAMI, JMLR, IJCV, PAA, CVPR
Tumor Deconvolution	Health	201920	DREAM	38 teams	2019 RECOMB/ISCB Regulatory and Systems Genomics, BiorXiv
AutoDL series (6 competitions so far)	Automated Machine Learning	2019-21	CodaLab	more than 300 teams	ECML/PKDD, ACML, NeurIPS, IJCNN, WAIC, IEEE TPAMI
Digital Mammography	Health	2017	DREAM	more than 120 teams	RECOMB/ISCB Regulatory and Systems Genomics
L2RPN	Energy	2020	CodaLab	more than 300 participants	NeurIPS, ArXiv
Challenge AI for industry	Aeronotic	2021	CodaLab	XXX	XXX

Table 1.1: Table of communities engagement

As a complement, a non-exhaustive list of conferences that have call for competitions, or can offer workshops and/or proceedings, as well as journals that can welcome competition result publication :

- *Conferences and workshops*: ESANN, ICMLA, WCCI (IJCNN, CEC), ECML/PKDD (Discovery challenges), KDD (KDD cup), CVPR, ECCV, ECML/PKDD, ICPR, ICDAR, IEEE international conference on big data, IEEE International Conference on Automatic Face and Gesture Recognition (FG), ACM SIGIR Forum, NeurIPS dataset and benchmark track, NeurIPS competition track, Workshops @ NeurIPS, ICML, AAAI, CVPR, ICCV, Workshop on Semantic Evaluation, etc.

- *Book series*: CiML Springer series, etc.

- *Journals and pre-prints*: International Journal of Forecasting, International Journal of Information Retrieval Research (IJIRR), IEEE Journal of Biomedical and Health Informatics, IEEE Access, Machine Vision and Applications, IEEE TPAMI, Nature methods, Nature communication, Journal of the American Medical Informatics Association, Journal of biomedical informatics, ArXiv, BiorXiv, PMLR, BMC bioinformatics, etc.

### 1.3 Costs, man power and resources

Depending on the model chosen by the organizer, various costs will be associated with a competition organization. Human resources will also have to be invested to guarantee the quality of the organized challenge. To mitigate the problem of financing a competition, diverse sponsors, private companies or academic institutions can be involved. In this section, we review the costs, the need in man power and the resources the resources that can be requested when organizing challenges.

#### An example of challenges costs: the L2RPN challenge / NeurIPS 2020

- **Research field** : Energy and environment.
- **Challenge platform** : Codalab<sup>a</sup>.
- **Duration of the challenge** : 4 months.
- **Number of participants** : 300.
- **Data generation, access and curation : costs and resources description** : 70,000 euros.
- **Challenge engineering : costs and resources description** : 120,000 euros.
- **Challenge design, scientific expertise : costs and resources description** : 170,000 euros.
- **Prices, travel, conference organization (approximate evaluation of costs)** : 30,000 euros.
- **Challenge governance (cost evaluation of legal, ethics and data privacy costs)** : none.
- **Dissemination** : RTE, Google Research, University College of London, EPRI, IQT Labs. Chalearn.
- **Sponsors** : PMLR<sup>b</sup> & ChaLearn<sup>c</sup>

<sup>a</sup> <https://competitions.codalab.org/competitions/25426>

<sup>b</sup> <https://arxiv.org/abs/2103.03104>

<sup>c</sup> <https://l2rpn.chalearn.org/>

#### 1.3.1 On overview of the requirements and associated costs

##### Platform and registration system

Several digital platforms can support challenge organization (see chapter 5 for different models of challenge platforms). Defining the platform should be a starting point of challenge organization, as open-source project such as CodaLab or commercial challenge platforms such as Kaggle will provide very different resources (technical support, engineering manpower dedicated to the competition...) and as-



Fig. 1.3: Costs of data challenge organization. Pictures adapted from: macrovector, alvaro\_cabrera, visnezh & vectorjuice open work on freepik

sociated costs. Please refer to Chapter 5 for more details on the different services provided by each platform.

### Data generation, access and curation

Good quality, well curated data is a key factor of a competition success. General cost evaluation of data generation is complicated because it is highly variable depending on the scientific discipline involved. Data generation has always a cost, but this cost can be supported by different players of the competition (sponsors, private companies, organisation committee, care providers, health insurance, etc). This costs also depends on the data type, size and accessibility. Data labelling can be achieved manually, using open source tools such as LabelMe, or private services such as Amazon

Mechanical Turk in computer vision<sup>3</sup> Good quality data also relies on the willing of organizers to work in synchronisation with the global efforts for technical standardization and ethic responsible data sharing, e.g. Global Alliance for Genomics and Health or FAIR principles for data management and stewardship [16, 17].

### **Governance and legal costs**

Competition governance strategy should also include legal counseling costs, that will ensure that the data storage and sharing concept complies with national and international legal requirements. In particular, usage of identifiable personal data (such as patient clinical data) is a complex and significant legal and data protection challenge [18]. Moreover, rules for awarding prizes and travel grants should be clearly defined, this includes definitions of :

- jury's composition (committee of experts)
- criteria of evaluation (e.g. relevance, usefulness, novelty, etc.)
- challenge submission process
- intellectual properties
- exclusion and appeal procedures
- control of the use of funds and goods, including prizes
- privacy policy
- errors, frauds and breaches of rules mitigation plan

### **Computation and storage**

The digital data challenge platforms rely on cloud computing services to run and evaluate models. Access to these services can be externalized (such as Google Cloud Platform, Openstack, IBM Cloud or Amazon web services) or provided internally using the computing infrastructure of the challenge organizers. Depending on the competitions, the problem to solve and the type of data, the required resources vary a lot. For instance, in the case of code submission, it is important to estimate well the number of participants, and sometimes to limit the entries by setting a hard threshold. Indeed, code submission offers many advantages (controlled environments, confidential data, good sharing of the resources among participants, etc.) but is computationally very demanding. Thus, the organizers must accurately estimate the computation time of the expected methods as well as the type of computing units to use ([19]), knowing that donation of cloud units from Google, Azure and Amazon are relatively easy to obtain. Some platform such as Codalab can be coupled with such cloud services, via the use of compute workers. Finally, they need to decide accordingly whether they wish to offer computational services (allowing code submission) or ask participants to provide their own computational resources (only allowing the submission of results).

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<sup>3</sup> A review of labelling tools can be found here: <https://neptune.ai/blog/data-labeling-and-data-collection>

### Scientific expertise, challenge design and engineering

Bringing together an expert steering committee is a key factor to ensure that the issue raised by the competition corresponds to the needs of the community, and that the data will be used correctly to ask the right question. These two points are essential to ensure community engagement and the quality of the competition. In some specific occasion, building a realistic environment to simulate the different tasks of a competition can required a lot of work (research and engineer manpower ahead of the competition). For instance, L2RPN competition series required the generation of a dedicated framework and the generation of synthetic data with several people working on the project for over a year (cost of  $\sim 200\text{k€}$ , see Table ??). Once the competition is completed, manpower is also needed to analyse the results, summarize, and disseminate the challenge outcomes.

### Prizes, Travel and conference organization

Reward costs should be included in the challenge budget. Prizes can be a important incentive to recruit participant (see section 1). . In case of in-person events, travel and conference organization costs should be considered. This can include speakers invitations, participation to the venue costs and travel grants for students. Example of costs to organized an event can be found in Table 1.2).

	Expense type	Estimated cost (EUR)
1	Invited speakers registration (4x\$250)	1,000
2	Organizer travel expenses (3x\$2000)	6,000
3	Lunch (catering) for 40*\$50)	2,00
4	Dinner for invited speakers/winners/organizers 20*\$50	1,000

Table 1.2: Conference or workshop organization for a total budget of 10,000 euros.

### 1.3.2 Man power

Man power is crucial in competition organization, and should not be underestimated. See Table 1.3 for an average estimation of man power required to organize a challenge.

H]

Task	Description	Hours
1	<b>Finding/reviewing data.</b>	50
2	<b>Formatting data.</b> Preprocess and format the data to simplify the task of participants, obfuscate the origin, anonymize.	100
3	<b>Assessment.</b> Define a task and evaluation metrics. Define and implement methods of scoring the results and comparing them.	50
4	<b>Baseline software; starting kit.</b> Implement a simple example performing the tasks of the challenge. Prepare useful software libraries, make examples.	100
5	<b>Result formats and software interfaces.</b> Define the formats in which the results should be returned by the systems and how experimentation will be conducted during the challenge.	50
6	<b>Benchmark protocol.</b> Define the rules of the competition and determine the sequence of events.	50
7	<b>Web portal.</b> Implement on challenge platform the benchmark protocol allowing on-line submissions and displaying results on a leaderboard.	25
8	<b>Guidelines to participants.</b> Write the competition rules, document the formats and the scoring methods, write FAQs.	50
9	<b>Beta testing.</b> Organize and conduct tests of the challenge.	25
10	<b>Run the challenge.</b> Answer participants, attend to the platform (2h/week).	100
11	<b>Prepare the workshops.</b> Write proposals. Look for tutorial speakers. Select speakers. Create a schedule. Advertise.	50
12	<b>Competition result analysis.</b> Compile the results. Produce graphs. Derive conclusions.	50
13	<b>Reports.</b> Write reports on the benchmark design, the datasets, and the results of the competition.	100
14	<b>On-line result dissemination.</b> Make available on-line the competition result analyses, fact sheets of the competitors's methods, and the workshop slides.	50
15	<b>Prepare workshop proceedings.</b> Solicit papers, organize the review process, and edit the papers.	100
16	<b>Distribute prizes and awards.</b>	10

Table 1.3: Evaluation of man power to organize a challenge (varies from challenge to challenge, should be estimated by the organizing team)

### 1.3.3 Resources: sponsors and grant agencies

As the global cost of competition organisation grows along with the complexity of the data and tasks, proposal and grant writing to find money is essential. By leveraging institutional support and sponsors, organizers will achieve good quality challenges and ensure community participation. More and more universities and

national funding agencies<sup>4</sup> or scientific societies<sup>5</sup> support competition organization. Building partnership with private companies<sup>6</sup> and involving collaborators in scientific consortium is also likely to be very helpful to reduce the financial barriers in organizing challenges.

## 1.4 Conclusion

In this chapter, we offer some tips and practical details for organizing successful competitions. In the first part, we review the different types of motivations that lead participants to participate in the challenge. Then, we offer advice on how to recruit the scientific community concerned and disseminate the challenge and its results. Finally, we review the different stages of preparation for a challenge, the associated financial and human costs, and the possibilities of fundings.

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<sup>4</sup> For instance the University College of London, the National Research Agency in France, the ETH in Switzerland, or the EIT Health in Europe

<sup>5</sup> National Science Foundation in the United States, the IEEE Computational Intelligence Society, or the International Neural Network Society

<sup>6</sup> Non-exhaustive list of potential sponsors: Google, Microsoft, Orange, Kaggle, Health discovery corporation



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