

IDIAP RESEARCH REPORT



BEAT: AN OPEN-SOURCE WEB-BASED OPEN-SCIENCE PLATFORM

André Anjos

Laurent El Shafey

Sébastien Marcel

Idiap-RR-14-2017

APRIL 2017

BEAT: An Open-Source Web-Based Open-Science Platform

André Anjos, Laurent El-Shafey and Sébastien Marcel

{andre.anjos,laurent.el-shafey,sebastien.marcel}@idiap.ch

Idiap Research Institute, rue Marconi, 19
Centre du Parc, 1920, Martigny, VS, Switzerland

April 7, 2017

Abstract

With the increased interest in computational sciences, machine learning (ML), pattern recognition (PR) and big data, governmental agencies, academia and manufacturers are overwhelmed by the constant influx of new algorithms and techniques promising improved performance, generalization and robustness. Sadly, result reproducibility is often an overlooked feature accompanying original research publications, competitions and benchmark evaluations. The main reasons behind such a gap arise from natural complications in research and development in this area: the distribution of data may be a sensitive issue; software frameworks are difficult to install and maintain; Test protocols may involve a potentially large set of intricate steps which are difficult to handle. Given the raising complexity of research challenges and the constant increase in data volume, the conditions for achieving reproducible research in the domain are also increasingly difficult to meet.

To bridge this gap, we built an open platform for research in computational sciences related to pattern recognition and machine learning, to help on the development, reproducibility and certification of results obtained in the field. By making use of such a system, academic, governmental or industrial organizations enable users to easily and socially develop processing toolchains, re-use data, algorithms, workflows and compare results from distinct algorithms and/or parameterizations with minimal effort. This article presents such a platform and discusses some of its key features, uses and limitations. We overview a currently operational prototype and provide design insights.

Keywords: Machine Learning, Pattern Recognition, Reproducible Research, Online Platform

1 Introduction

One of the key aspects of modern computer science research lies in the use of personal computers (PCs) either for the simulation of known phenomena or for the evaluation of data collected from natural observations. Mashups of these data, organized in tables and figures are attached to textual descriptions leading to scientific publications. Frequently, data sets, code and actionable software leading to results are excluded upon recording and preservation of articles. This situation slows down potential scientific development in at least two major aspects: (1) re-using ideas from different sources normally implies the re-development of software leading to original results and (2) the reviewing process of candidate ideas is based on trust rather than on hard, verifiable evidence [1].

The need and benefits for reproducibility in computational science was already recognized by academia [2, 3, 4] and industry [5], though concrete actions to overcome inherent difficulties are yet to appear into *de facto* standards in this field. For example, it has been shown by MIT researchers [6] that the reviewing process that determines article acceptance in some conferences may be tricked by publications with machine generated content.

While scientific articles normally incorporate a stage of certification referred as peer-reviewing, the very same software frameworks and data leading to the stated conclusions, *when available*, are considered as a bonus and dismissed unreviewed. Even if knowledgeable reviewers can predict when written material is insufficiently discussed or poorly argued, one must also consider the hypothesis of rich arguments being coupled to poorly executed software implementations and data quality ending up in misleading conclusions, which do not translate in scientific development. It is a fact that correct and repeatable execution of software

over data does not guarantee a good trend either, but less so does just an article. Only by coupling scientific reports, software and data to the extensibility and reuse which is required to verify evidence, can society achieve a faster and steady pace of development. Reproducibility and certification, in this context, should become a must for the future of artificial intelligence rather than a mere bonus.

Publication of research results is not the sole place where advances are needed. The conception of ideas, their embodiment in the form of computer routines and experiments, as well as the actual reviewing process could also benefit from technological advances in computer cloud infrastructures, programming tools (e.g. Web 2.0) and social networking. Albeit limiting, technological challenges do not hold exclusivity in irreproducibility. Many research domains such as those related to medical, biometrics and forensics applications also face legal barriers. Data used in these domains should be handled according to stringent law requirements related to human rights for privacy, which poses obstacles to reproducibility, but also knowledge sharing.

1.1 The *Status Quo*: what can we do better?

The idea behind a platform for the evaluation of reproducible machine learning and pattern recognition algorithms is not new. Software-based frameworks currently exist in different implementation languages and to attend different purposes. The current main trend seems to be biased towards the creation of web services that ease the management of challenges in machine learning and pattern recognition [7, 8] instead of run-yourself software solutions which were very popular in the last decade. Web services can offer convenient access through different types of devices (computers, tablets and mobile phones), while requiring only a compatible web-browser to be installed on the user machine. With the advent of modern web programming techniques and useful libraries, there is virtually nothing one cannot do through a browser window.

One of the key issues with leading platforms on this market is that of data sharing and privacy. At the same time reproducibility in computational science calls for open data access, certain research domains must respect privacy considerations when sharing data. With new EU privacy law requirements well on the way [9] and matching agreements being reached with other leading countries, personal data transfer must respect formal conditioning and safe keeping - for example, biometric data may be accessible only via end-user license agreements which, typically, disallow copying outside institutional premises. Such a trend will directly influence how research is able to access and share data which, in turn, will impact the adoption of existing solutions. In practice, platforms tackling research reproducibility must incorporate privacy by design¹ (PbD) on their blue prints. PbD can be beneficial to key players in academic domains in which data is not easily transferable, but also to improve the relationship between those, industry and governmental agencies which are also key players in research.

When one talks about research in machine learning and pattern recognition, they must not forget difficulties related to the implementation of its software building blocks, required for the needed repetitive testing, evaluation and performance tuning leading to discovery and reading material. Each of those blocks is implemented over and over using fashionable languages and paradigms through time, existing in a format which becomes outdated as new fashions and paradigms appear. At a point in time, the FORTRAN language was considered the *de facto* scientific programming tool. After that Matlab and nowadays a myriad of options exist to encode knowledge in this domain. You must have asked yourself many times “Which to pick?”. Because no right answer is on the horizon, solutions must also take into consideration the hybrid nature in this research domain. Building workflows require tools from a variety of languages to co-exist through time to build the perfect re-usable machinery.

In the remainder of this article, we introduce the BEAT platform,² a PbD-built architecture to take on these issues: social development, hybrid algorithm re-use, open-sourcing and confidentiality, providing a new paradigm for the development and evaluation of pattern recognition tools. We present the platform design in Section 2, outlining its main components and core technology. In Section 3 we exemplify how it can be use to address data-driven problems in computational science through different use-cases in education, challenge preparation and industry-academia relationship. Finally, at Section 4, we conclude the article with a summary of platform limitations and a look into its future.

¹https://en.wikipedia.org/wiki/Privacy_by_design

²Operational at <https://www.beat-eu.org/platform/>.

2 The BEAT Platform

BEAT is a pan-european project composed of both academic and industrial partners in which one of the goals was the design and development of a free, open-source,³ online web-based platform for the development and certification of reproducible software-based machine learning (ML) and pattern recognition (PR) experiments. The main intent behind the platform is to establish a framework for the certification and performance analysis of such systems while still respecting privacy and confidentiality of built-in data and user contributions. The framework, as per definition, is task-independent, being adaptable to different problem domains and evaluation scenarios. At the conceptual phase, the platform was bound to support a number of use-cases which we try to summarize:

- Benchmarking of ML and PR systems and components: users should be able to program and execute full systems so as to identify performance and computing requirements for complete toolchains or individual components;
- Comparative evaluation: it should be possible to run challenges and competitions on the platform as it is the case in similar systems such as Kaggle [8];
- Certification of ML and PR systems: the platform should be able to attest on the operation and performance of experiments so as to support the work of certification agencies or publication claims;
- Educational resource: the platform shall be usable as an educational resource for transmitting know-how about ML and PR applications. It should be possible to set-up interest groups that share work assignments such as in a teacher-student relationship.

2.1 Application Breakdown

The BEAT Platform is composed of three main applications: the web, the scheduler and one or more worker nodes. The main function of the web application is to handle authentication and authorization, while the main function of the back-end (scheduler and worker nodes) is to handle the execution of the experiments. Figure 1 shows the high-level interaction between those three applications.

The web application is the main entry point of the platform. It consists of two different major components: a set of **Web Application Programming Interfaces (API)** and a **User Interface**. The BEAT Web API provides a set of entry points that can be used by external applications that wish to communicate with the platform, e.g. to get the status of a given experiment. This Web API is implemented as a RESTful API using the popular Django web framework [10]. On top of this API and also written using Django, a browseable user interface has been built, allowing a user to interact with the platform via a conventional web browser and to make use of the different functionalities provided by BEAT, such as implementing algorithms, starting an experiment or comparing a set of results (see Figure 2). The RESTful API also allows third-party applications to be developed in order to complement the user experience, for example, using smart phones or tablets.

The execution of experiments triggered via the web application is performed on one or more **workers**, which form the computation back-end. Job assignment is intermediated by a central **scheduler** process that assigns computing jobs to different nodes available respecting user quotas and hardware requirements. To achieve this flexibility, the BEAT back-end closely resembles typical batch-queue submission systems,⁴ such as the Oracle Grid EngineTM or TORQUE and organizes its workers into processing queues. Each BEAT user can then assign whole experiments to such queues or individually define which resources each bit of an experiment must use. This technique allows for experimental toolchains which are composed of an heterogeneous pool processing environments composed of software libraries and hardware resources.

2.2 Object Model

All interactions between the web and the backend are done using an abstract object model representing an experiment and associated components, that was specifically crafted to represent machine learning and pat-

³Source-code: <https://gitlab.idiap.ch/beat/>

⁴Batch queuing systems: https://en.wikipedia.org/wiki/Job_scheduler

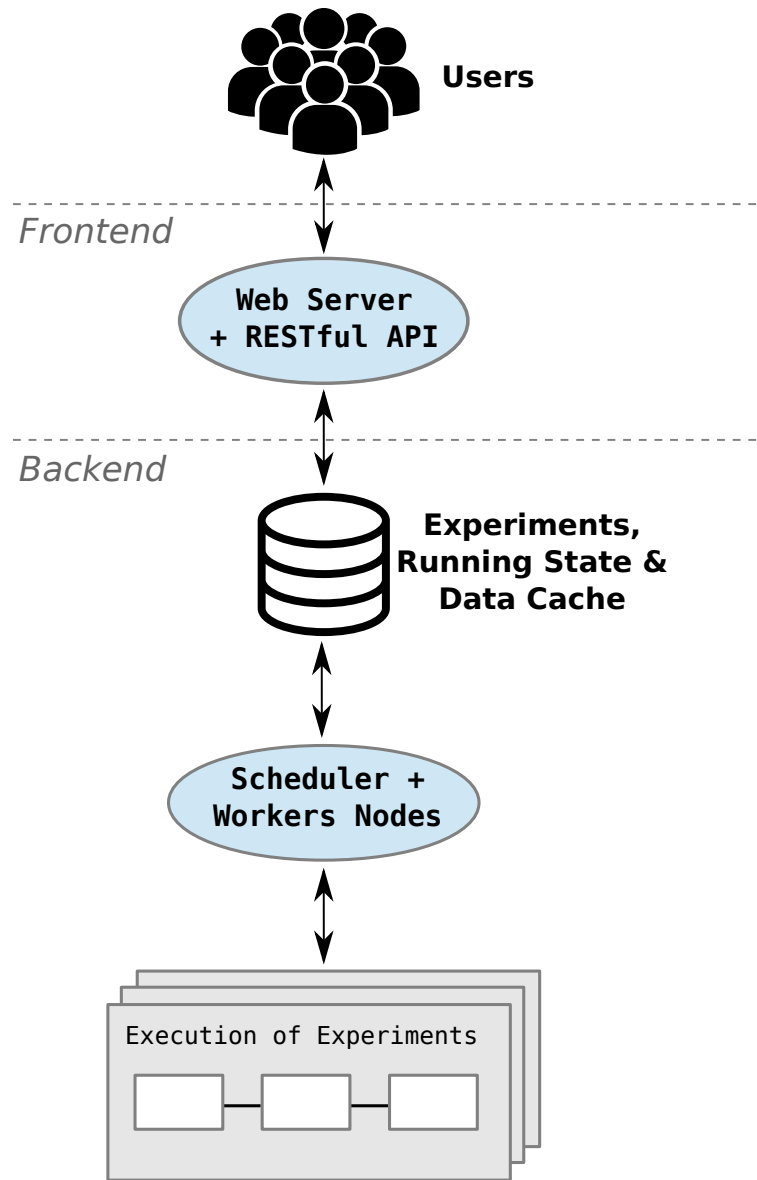


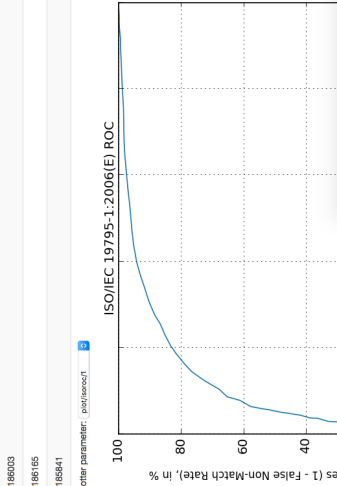
Figure 1: An overview of the BEAT platform applications and their interaction. Users use the web front-end to run experiments, search and combine results. A back-end handles the execution of experiments on dedicated hardware.

The BEAT platform attests that the following results were obtained by an experiment performed on our servers. We kept all the details needed to reproduce them (touchain, database, algorithms, libraries, dataformats and the actual experimental setup).

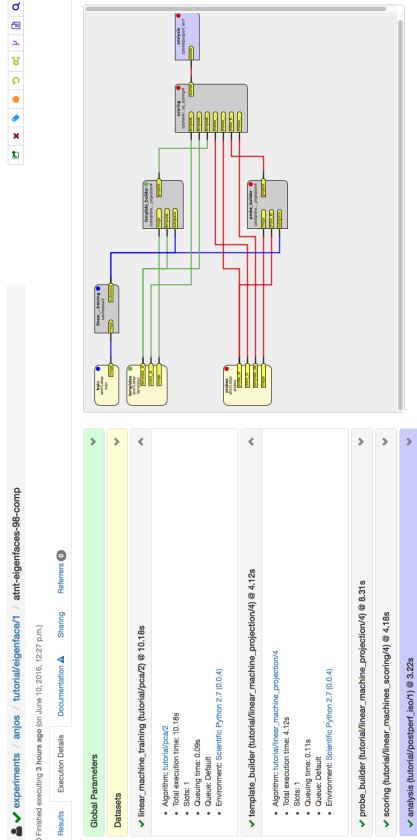
- Published 3 months, 3 weeks ago, on Feb. 13, 2016, 8:37 a.m.
- Experiment: robertodaza:robertodaza:compensator_180218200018:Competition_Baseline_Modified_Scaled_Mantissa_Distance
- Description: This experiment is an example for Negative Scenario Ongoing Competition (NSOC).

Results Touchchain Documentation

Outputs for block analyzer_private



(b) Attestation



(a) Experiment view

Configuration

You may add more filtering criteria by clicking on the + buttons. Search filters are applied using a logical-AND operator (the more, the stricter the criteria will be). In order to search using a logical-OR, add search terms to the text boxes separated by a single comma. Eg.: "eigenface.fisherface" (meaning search for eigenface OR fisherface). Click on the x buttons to remove a given search criteria. Click on the "Update" button to update the result display. If you're logged in, you may also hit on "Save" to save your search filters and re-run this search again on the future.

Any fisherface anywhere

trial contain

substring

eigenface

Database names

trial contain

substring

attn/3

Update Save

Successful Experiments 10

Touchain: tutorial/eigenface/1%

Protocol: attn/3@clap%

Analyzer: tutorial/postper_1iso/1%

Add to report

	Updated	Name	frr	eer	roc	far
<input type="checkbox"/>	Feb. 17, 2016	anjos/tutorial/eigenface/1/attn-eigenfaces-5-comp-v2	0.06	0.06	0.06	0.06
<input type="checkbox"/>	Feb. 17, 2016	anjos/tutorial/eigenface/1/attn-eigenfaces-5-comp	0.06	0.06	0.06	0.06
<input type="checkbox"/>	June 10, 2016	anjos/tutorial/eigenface/1/attn-eigenfaces-98-comp	0.07	0.0718421	0.0728842	0.08
<input type="checkbox"/>	June 10, 2016	anjos/tutorial/eigenface/1/attn-eigenfaces-48-comp	0.08	0.08	0.08	0.08
<input type="checkbox"/>	May 17, 2016	anjos/tutorial/eigenface/1/attn-eigenfaces-35-comp	0.08	0.08	0.08	0.08
<input type="checkbox"/>	May 12, 2016	anjos/tutorial/eigenface/1/attn-eigenfaces-34-comp	0.08	0.08	0.08	0.08

(c) Search view

(d) Scheduler control page

Scheduler Version: 1.0.0 (updated: 15:33 +0200, 10th June 2016)

Wipe cache Re-configure Cancel Experiments

Status 0 Experiments 0 Workers 40 Queues 5

Cache Occupancy (in Mb)

Total disk space: 4864 Gb

Used (18%) Free (82%)

Experiments

Running	Completed
0	0

Jobs

Queued	Running	Completed	Failed	Cancelled
0	0	0	0	0

Figure 2: BEAT web user interface. (a) Experiment view: after experiment execution, the user can check experimental details such as the results, but equally computing performance indicators; (b) Attestation: Each experiment may be certified by the platform guaranteeing its reproducibility and make it read-only; (c) Search and Reports: Experimental results from different experiments may be combined into powerful reports that can be exported into publications; (d) Scheduler: the backend, composed of workers attached to processing queues can be monitored and controlled by platform administrators.

tern recognition problems. By configuring an experiment, a BEAT platform user puts together a **toolchain** (see drawing at Figure 2a), **databases** and **algorithms** that produce the desired test setup.⁵

A toolchain (or workflow), defines a sequence of interconnected blocks that can perform a certain task (e.g. face recognition using eigen-faces). Each connection in a toolchain defines a distinct strongly typed data flow path, and determines the overall execution order for the blocks. What is not determined by the toolchain is which algorithms execute in each block or what is the input database. Once a toolchain is defined, the BEAT platform provides an easy to use web-based experiment configurator (see Figure 3) that allows the user to hand-pick algorithms and databases that fit together respecting the block configuration, input and output data format exchange between the block being configured and its surrounding siblings.

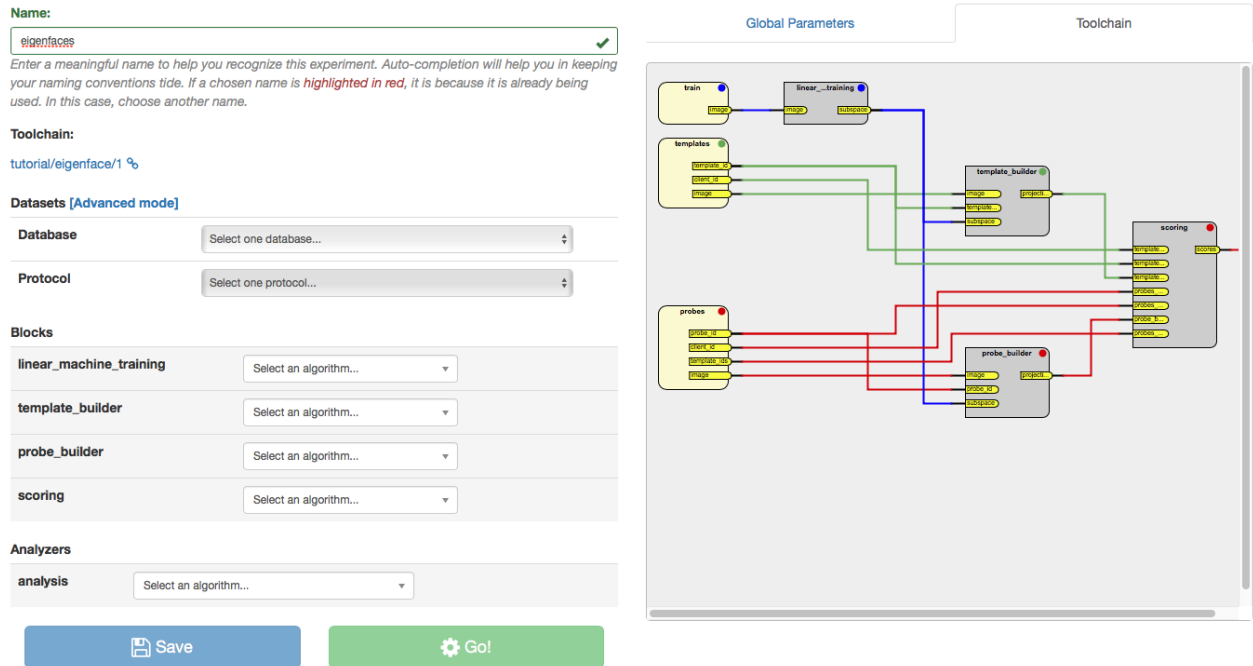


Figure 3: The BEAT platform experiment configurator allows the user to easily associate databases, algorithms and analyzers together to create the desired setup. As the user chooses components for the toolchain, choices of further components are restricted respecting data format compatibility between the blocks.

To implement this feature, the core object model defines **data formats**, which are user defined data structures implementing the atomic data elements that are exchanged in block connections (see more details in Figure 4). When the user hand-picks a particular database for the input of an experiment, such a database will yield data elements of a certain type through its fanouts which limits the choices for the input blocks containing user code. In the same way, each user algorithm defines input and output data types, that impose requirements on downstream blocks. The experiment configurator takes advantage of this feature, coupled with the algorithms and databases structure (number of fan-ins and fan-outs) to only provide possible combinations during experiment setup, improving user experience with the platform.

Each input data block in a toolchain (blocks on the left in Figure 3) outputs data through one or more channels that are synchronized with each other. This technique makes it possible for a database designer to determine which data points must be served together respecting data restrictions (e.g. associating labels to samples). Each block also determines what is the synchronization channel it will work on. Data is then fed into the algorithm via the block fan-ins in a paced manner, respecting the original database designer usage protocols. This technique allows the user code to be programmed loop-free, since iteration is carried out by the platform itself.

A less obvious yet powerful advantage of this approach is automatic parallelization. Because the platform controls input data iteration, it is possible to split processing in N-folds potentially speeding-up data

⁵User guide: <https://www.beat-eu.org/platform/static/guide/index.html>

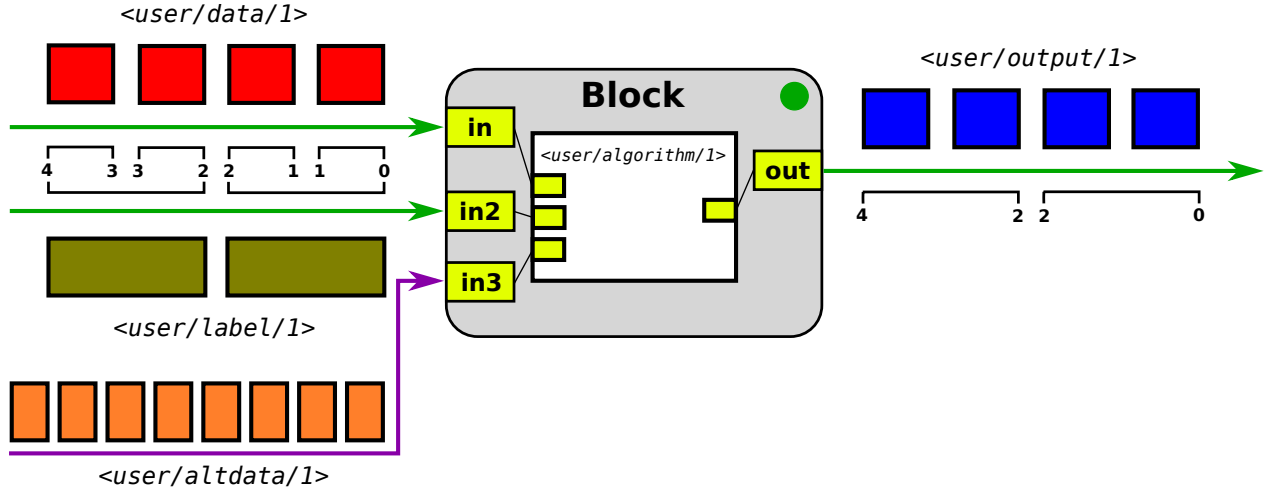


Figure 4: Schematic diagram showing the input of a block, composed of different types of objects which are defined by 3 different *data formats*, called *user/data/1*, *user/label/1* and *user/altdata/1*. Inside the block, an algorithm may be installed for as long as it can input those data types. The block fanout data type is determined either by the output type of the algorithm which, in turn, imposes a restriction on the downstream block algorithms that can be installed. Some inputs and the output of a block are automatically synchronized together so the BEAT platform is aware of the relationship between original data and the outcome of each block in an experiment.

processing without user intervention.

2.3 Back-end

After the experiment is properly configured, it may be stored or scheduled for execution in the platform processing farm. To address that, a scheduler application breaks down the execution path and order respecting the experiment's block boundaries. Each algorithm-equipped block is then executed in a single isolated process, inputting data from the previous block and outputting data that is stored into a common, large filesystem based cache. The BEAT platform cache serves two purposes: (1) it optimizes data processing allowing scheduled experiments to skip blocks which have already been processed before, in the context of the same experiments or on identical conditions, and (2) it isolates inter-block (read process) communication, effectively allowing for a simpler programming interface while retaining the possibility to execute each block process in any combination of hardware and software resources available. In this context, it is possible an experimental setup is effectively run in a multitude of different environments, e.g., preprocess images using a python encoded algorithm running on a Linux workstation, but train a deep convolutional neural network in the next block using a graphical processing unit (GPU) driven by the Caffe, Torch, or TensorFlow frameworks [11].

To keep resources under control in the back-end processing farm and implement fair use and sharing, each available compute node (**worker**) is allocated to a queue which is subject to usage restrictions. Each queue determines the maximum memory, number of compute threads and the maximum time any given user process may consume on any given worker belonging to it. Queues may be shared among users or groups of users inside the platform giving an administrative authority the possibility to effectively control resource usage through the system. When users configure an experiment, they must determine which processing queues and software environments will be used for each block. A global default is provided to simplify the configuration process for the most obvious cases. Any number of user experiments can be scheduled without limitations. Execution, on the other hand, is subject to resource availability and priority.

2.4 Privacy, Certification and Versioning

The BEAT platform implements a mechanism to control user data confidentiality and access based on access permissions which are user-configurable. By default, all user interaction with the platform is kept confidential to users until they wish to allow access to other parties. The level of control on object access permissions remotely resembles that of the file systems of UNIX-based operating systems. Users may allow other users or groups (called **teams** at the platform) to view or execute algorithmic code, access experimental results, toolchains, search queries, data formats, etc. Teams can be created by users to provide homogeneous access permissions to groups of users to a certain resource. This feature allows users to share experimental details between groups of interest (e.g. while building a scientific article), while keeping it confidential from the general public visiting the platform.

Once experiments were successfully run, their output (scalars and plots) may be used in scientific publications. To ensure reproducibility, the BEAT platform implements a unique attestation mechanism⁶ that provides an assurance to peer-reviewers and interested parties all bits making up an experiment (toolchain, algorithms, data formats and data sets) won't be modified any longer and can be re-used for verifying results or recombined in new experimental settings. By creating an attestation, users freeze experiment details altogether (no elements can be further edited), while allowing anonymous access to most data. Attestation effectively makes toolchains and data formats used in an experiment public. Algorithms may be set executable-only which allows peers to re-run the experiment but no direct access to the source code.

While attested experiments cannot be any longer modified, it is still possible for users to create new versions of individual components by copying existing material available. New versions are tracked by the platform, which records code re-use and can therefore potentially be used to trace original authorship.

Databases: One important aspect on data privacy may concern raw input data, that is finally fed by the BEAT platform backend into experiments. Databases in sensitive areas such as those related to biometrics, forensics or biomedical applications, may require special end-user license agreements that require data in its original or processed forms is not exported from the peer institute premises.

To comply with such requirements, the BEAT platform is designed taking privacy as a very strong and important operational constraint. Only platform administrators are allowed to physically copy raw data sets into the platform file systems. Once such data sets are in place, administrators create special algorithms that explain how to read data from disk and feed it into user toolchains while respecting usage protocols defined by the original data controller. Such special algorithms are called **views** and behave in a similar way to user algorithms. Users are allowed to plug in one or more database views into experiments effectively defining the input blocks of the experiment. Because intermediate data output by processing blocks cannot be exported, data privacy is guaranteed.

3 Applications

In its current state, the BEAT platform can honour a large number of use cases in pattern recognition and machine learning applications through the use of its built-in experiment running facilities, certification mechanisms and storable searches terms. In this section, we investigate a few of these use-cases and how BEAT provides an answer to hosting challenges (competitions) or can be made useful in industry-academia relationships.

3.1 Use-case 1: Cooperative academic work

Development of new techniques and ideas in academic work very often is the result of team work. Two colleagues studying a particular subject may be on the same academic premises or apart, in completely different institutions. Ideas are exchanged via e-mails and virtual meetings, a common software framework is selected as a method for sharing implementations and analysis is carried out by the exchange of simple scalars, tables and, frequently, graphics comparing results of experimental setups. Go/no-go decisions are taken in group as part of the analysis process, which typically involves an even greater number of persons (e.g. research supervisors). The BEAT platform can be used in this context to ensure that the same

⁶US patent filed under the number US20150970333

software environment and analysis is executed for all experiments leading to a scientific report, guaranteeing homogeneity and reproducibility at all times.

After databases are installed into the platform, one of the parties in the academic team creates (or copies) algorithms, toolchains and experiments that represent the state-of-the-art baseline systems one wishes to improve upon. At this point a clear set of metrics is defined leading to scalars and figures which should be generated on a per-experiment basis. These elements are then shared via the BEAT team feature so that only people in the academic pool of interest have access to core elements of the study and end results.

A search term is then created by a team member (and shared) such that it is possible to keep track of advances when comparing various experiments together. Figure 5 shows an example search filter setup on the BEAT platform, exemplifying a possible setup. The saved search query can be completed with a rich text description. Users have the ability to control which analysis figures to display in the aggregation table and plots. An unlimited number search terms may be stored to express different analysis points of views. For example, it would be possible to setup a search query that would compare the user current work against other algorithmic approaches or, in another instance, how the new user setup improves across databases or different parameter sets.

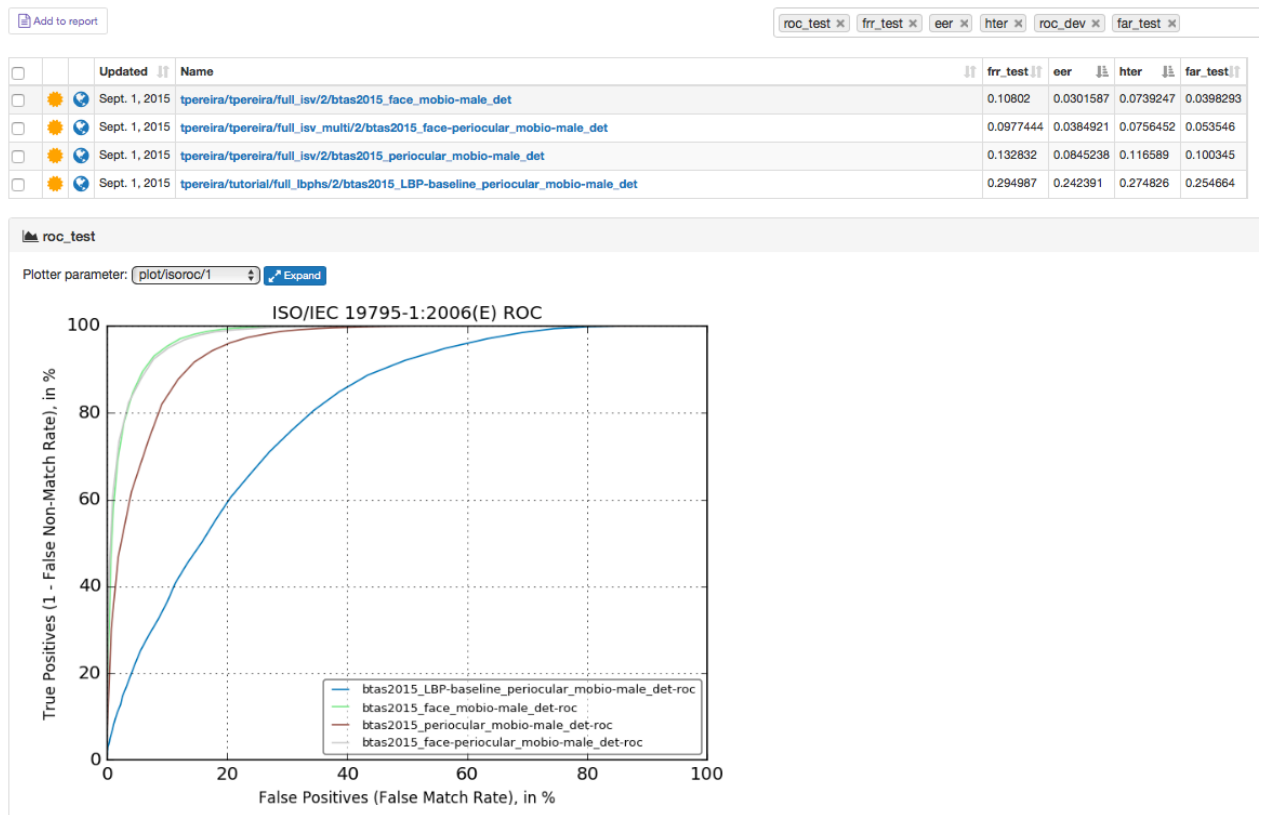


Figure 5: Example of tables automatically generated by the BEAT platform via its *search* feature. It allows you to store specific search terms that result in scalars and figures from the selected experiments to be compared. The user can select how to display the figures associated with their analysis metrics, how to sort and which columns to show on the comparison table. Available online via https://www.beat-eu.org/platform/search/tpereira/btas2015_mobio_male/. The resulting report can be found at <https://www.beat-eu.org/platform/reports/751803513/> and provides assurance experiments in the paper are reproducible.

Once a conclusion has been reached and a scientific report needs to be generated, it is possible to attest all experiments together through BEAT platform *reports*. A report can be thought as a *macro-attestation*, certifying multiple experiments together in a single place. Reports can also be decorated with documentation, can contain tables and figures and be locked for external peer-reviewing, giving an assurance of reproducibility

to external reviewers and the research team.

3.2 Use-case 2: Challenges and education

It is a common practice in statistical pattern recognition research domains to setup challenges in order advancing research for specific goals. For example, in the area of Biometrics, most large conferences contain specific sessions for competitions organized to, for instance, improve the state-of-the-art in biometric authentication, identification, *spoofing* detection or pre-processing techniques. An academic or industrial partner sets up the competition defining one (or more) databases that will be used for the challenge, together with usage rules that must be respected by all participants. In common practice, final evaluation samples are normally not provided from the begin of the competition, to avoid bias in the final results.

The BEAT platform is a challenge-ready system requiring minimal management intervention during the course of the competition, from the part of the organizer. After databases and usage protocols are properly installed, the competition organizer may define baseline toolchains, algorithms and an analysis metric that will be provided to participants. A search query may then be stored which may define the criteria that must be respected in the competition. For instance, participants may be required to use a particular toolchain, algorithm, database version and/or protocol in their submissions. As the competition advances, the competition organizer may resubmit the store search query that will display an updated version of the leaderboard. The last step can be automated by the platform (via a specific *leaderboard* checkbox) and, in this case, competition organizers will receive an e-mail each time the search results for a stored search query changes. Competitors, when ready, share back their algorithm implementations with the organizer, that then can visually compare results through their stored search query. By design, entries originating from violations of the established competition rules simply do not appear in the defined leaderboard. The recently organized Keystroke Biometrics Ongoing Competition (KBOC) is an example of challenge using the platform.⁷ Final competition results were published in [12].

The BEAT platform may be equally used as an academic resource in a teacher-student relationship, in ways very similar to the organization of a competition. In this use-case, teachers define a task using the BEAT platform and may ask students to fill-up algorithmic details for exercising or for grading. As students finish their assignment, they can share back their work with the teacher using the specific sharing features of the platform.

3.3 Use-case 3: Industry-Academia interchange

Industry and academia often work on similar research topics. More specifically, an industrial partner may be interested in evaluating a technique developed by researchers in academia, before considering its potential exploitation.

Unfortunately, there may be several practical issues preventing a fruitful collaboration. First, the industrial world is always eager for incremental deliverables, before making the decision of pursuing or stopping a collaboration. This is not always easy when the company and its academic partner have completely different engineering processes. Second, a company may want to know how much better a system is before negotiating a license for its commercial exploitation. However, the company may be unable to share a dataset because of legal and/or privacy concerns. Third, technology transfer is often a difficult process where discrepancies may emerge due to misunderstandings on how to evaluate a technology and on which metrics and evaluation protocol to use on a given dataset. Finally, it may be difficult for an industrial partner to modify and re-evaluate a delivered prototype on another dataset, since an employee has to figure out how the prototype can be used and how to evaluate it on a given dataset. At the end, all those difficulties may negatively affect the decision of a company to engage with an academic partner.

The BEAT platform provides several features that address many of the above mentioned issues. Typically, the industrial partner would first set up a BEAT platform instance installed within its premises. Then, the database for the project is setup, and well defined evaluation protocols are implemented after a joint agreement between both parties. All of this successfully addresses the issue of giving an access to evaluate a prototype on this database to external partners, while keeping the data sequestered to respect legal and privacy concerns. The next step for the industrial partner is to implement a baseline system on the platform,

⁷https://www.beat-eu.org/platform/search/aythamimm/KBOC16_COMPETITION_SEARCH/

allowing the academic partner to better understand what kind of prototype is expecting from him, as well as one (or several) analyzers that implement metrics and the visualization tools required to evaluate a system. Besides, the industrial partner may clearly indicate to the other party which components they are allowed to change on the system. It can be an algorithm on a given box or the whole toolchain and associated algorithms depending on the project requirements. Analysis should be preserved as that corresponds to the metric of interest to the industrial partner. The academic partner then starts to upload prototypes until the project ends or the goal is satisfied. Benchmarks tell the academic partner how much close to the goal they are. Industrial partner gets a working, reproducible prototype at all times.

4 Conclusions

The BEAT platform is an open-source software platform for data researchers and data owners, which allows executing and evaluating algorithms on image, audio, video, or multi-dimensional data sets. It can host data that cannot be distributed by conventional means, either because of their large size or because of confidentiality constraints (or both). It offers data-owners the possibility (in agreement with the researchers) to select the processing pipelines most appropriate for their needs, while offering researchers access to big data while minimizing the legal hassles, risks, and cost that accompany conventional data sharing and that currently hamper the research community to fully contribute to solving challenges associated to big data. The software stack of the platform is composed of nearly 80'000 lines of code (Python: 58%, Javascript: 24%, HTML: 15%, CSS: 3%).

Despite the large number of features, the BEAT platform also presents limitations and therefore a lot of potential for improvements. Work leading to a more useful platform still needs to address the following issues:

- Multi-site scalability: Platforms running on different sites cannot currently communicate between each other. Effectively, it is both impractical and expensive to keep copies of large datasets in every institution where research is being conducted. It implies redundant expenses and may lead to reproducibility issues due to incomplete datasets existing in various places as a result of lack of resources or human errors;
- More backends: As of today, only a Python processing backend is implemented and available on the platform, allowing user algorithms to be programmed on. This may be considered an important limitation for different research labs in which other programming backends are used (e.g. Matlab, R, Julia, privately compiled binaries, etc.). A possible model to be adopted in this case is that of running user code in containers or virtual machines, which are isolated from the BEAT infrastructure. With such an approach, one may introduce flexibility while also enforcing security constraints;
- Development and debugging of experiments: Finally, current provisions for developing and debugging code for the BEAT platform could be improved. The migration from a desktop typical research environment into the web-based system may prove difficult for inexperienced users. A system to export and run BEAT experiments on someone's computer is available. Unfortunately, it requires users install raw data and a compatible software stack to make it functional, which can be considered a complex task. Work in this context should try to reduce or completely remove this entrance barrier by providing a development environment where experiments can be executed w/o requiring the user to manage software stacks while still allowing full control of the code flow in order to craft new components or debug existing ones.

We continue to develop the platform towards these goals and welcome new groups and partnerships to enlarge the domains of application of our currently operational prototype.

5 Acknowledgements

The research and development required by the platform and leading to this article has received funding from the European Community's FP7 under the grant agreement 284989 (BEAT) and from the Swiss Center for Biometrics Research and Testing (www.biometrics-center.ch).

The authors would like to thank also all the talented engineers from the Idiap research institute: Philip Abbet, Samuel Gaist, Flavio Tarsetti, Frank Formaz and Cédric Dufour. Without their help, an operational platform would not have been possible.

References

- [1] K. Price, “Anything you can do, I can do better (No you can’t)...,” *Computer Vision, Graphics, and Image Processing*, vol. 36, pp. 387–391, 1986.
- [2] M. Baker, “1,500 scientists lift the lid on reproducibility,” *Nature: International Weekly Journal of Science*, vol. 533, May 2016.
- [3] B. R. Jasny, G. Chin, L. Chong, and S. Vignieri, “Again, and again, and again...,” *Science*, vol. 334, no. 6060, p. 1225, 2011.
- [4] P. Vandewalle, “Code sharing is associated with research impact in image processing,” *IEEE Computing in Science and Engineering*, vol. 14, pp. 42–47, July 2012.
- [5] “Executable paper grand challenge.” <http://www.executablepapers.com/>. Accessed: 2016-06-10.
- [6] “Scigen.” <https://pdos.csail.mit.edu/archive/scigen/>. Accessed: 2016-02-11.
- [7] “Codalab: Accelerating reproducible computational science.” <http://codalab.org/>. Accessed: 2015-12-14.
- [8] “Kaggle: The home of data science.” <https://www.kaggle.com/>. Accessed: 2015-12-14.
- [9] “Reform of eu data protection rules.” http://ec.europa.eu/justice/data-protection/reform/index_en.htm. Accessed: 2016-06-10.
- [10] “Django: The web framework for perfectionists with deadlines.” <https://www.djangoproject.com>. Accessed: 2016-06-10.
- [11] S. Bahrampour, N. Ramakrishnan, L. Schott, and M. Shah, “Comparative study of caffe, neon, theano, and torch for deep learning,” *CoRR*, vol. abs/1511.06435, 2016.
- [12] A. Morales, J. Fierrez, M. Gomez-Barrero, J. Ortega-Garcia, R. Daza, J. V. Monaco, J. M. ao, J. Canuto, and A. George, “Kboc: Keystroke biometrics ongoing competition,” in *8th IEEE International Conference on Biometrics: Theory, Applications, and Systems*, 2016.