

Eidgenössisches Departement für Wirtschaft, Bildung und Forschung WBF

Kommission für Technologie und Innovation KTI

Förderagentur für Innovation

CTI funding application	PROJECT NO:	REF:	Co-Ref:
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Project Title

1 - 2 lines for publication purpose

R and D project: Deep Networks as a Semantic Platform for Modeling User Behavior Data

Project Title in English

Deep Networks as a Semantic Platform for Modeling User Behavior Data

Subject of project/Short description

Max. 480 characters for publication purposes

We propose to build a software platform for modeling, integrating, and utilizing data collected from user interactions in an online setting. Deep networks are used as a modeling framework along with existing highperformance computational frameworks. Data coming from different modalities are semantically integrated into a common embedding space. This supports predictive tasks from personalization and content recommendation to ads targeting and optimized bidding.

Project partners

* Required fields

Project partners listed on these first pages will be asked to sign the CTI contract and therefore need to have power of signature.

Main research partner (contact for all written communication; i.e. decision)

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Main implementation partner

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Trade	Softwar	e, Big Data			Numbe	er of emplo	yees:	8		

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Additional Re	esearch- and	Implementat	ion partners			
Research partn	ıer					
*Surname			*First name			Title/gender
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Website / *E-mail:			*Tel.:			
Trade:		Number of employees:				

As a rule, contributions made by implementation partner must cover at least 50% of total project costs. Exceptions to this rule may be made by virtue of art. 30 of the Ordinance on the Promotion of Research and Innovation (RIPO, SR 420.11) (http://www.kti.admin.ch)

199400

375368

CHF 175968

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CHF

Requested grant funding

Total project cost

Contribution from implementation partner

Areas of funding and disciplines Please choose only 1 discipline

Life	Engineering Sciences	Enabling	Micro- and
Sciences		Sciences	Nanotechnologies
□ Biotech □ Medtech □ Foodtech □ Agrotech □ Other Life Science technologies	☐ Production technologies ☐ Material technology ☐ Machines, Mechanical engineering ☐ Electrical engineering ☐ Civil engineering ☐ Chemical engineering ☐ Environmental technologies Ecology	□ Business management and finance □ Public management / Tourism / Urban planning □ Design / Art / Architecture □ Economics / Social sciences / Public health □ Information- and communication technologies (ICT) □ Integrated production / Logistics	□ Electronic components and systems, embedded systems □ Energy management: power electronic, building control components, energy harvesting □ Optoelectronic / photonic components and systems □ Sensors and actuators □ Micro and nano systems, measurement technology □ Materials, surfaces and interfaces □ Semiconductor fabrication, assembly, packaging □ Energy components and systems: Photovoltaics, solar thermal, fuel cells, wind energy □ Energy conversion and storage □ MEMS & MOEMS & BIOMEMS components and systems

Additional information

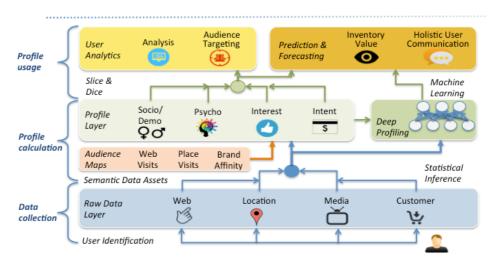
ш	on start-up company. Phase, please select
	Name of CTI-Coach: ☐ has read application
	CTI Network (NTN): please select
	Does this project cover one of the thematic topics of a Swiss Competence Center for Energy Research (SCCER) and is the Main Research Partner an academic research partner of this SCCER? If yes, please select.
	Is one academic research partner of (another) SCCER participating in this project? If yes, please select.
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	Preliminary guided patent search IPI (Swiss Federal Institute of Intellectual Property) completed
	Continuation of Innovation Cheque No:
	Continuation of SNSF Project: please select
П	International project: EUREKA Other:

1. What are the commercial goals and the deliverables of the proposed project (quantitative and measurable)? Have market and competitors studies been performed (enclose business plan if appropriate; see Note "Commercial goals")

Introduction. In a world that goes digital, better exploiting data in the value chain of a product or service is an important challenge for many companies across industry verticals. Specifically, this includes many sources of behavioral user data such as web visits, media consumption, app usage, location data, transactions, and a rich set of CRM data. Often such user data are acquired in semantically rich contexts, i.e. in settings where users interact with textual or media content, and where the interpretation of user actions hinges upon an understanding of the content users interact with. It is important to retain this context in order to make sense of these data. The scenarios in which such semantically rich data arises are diverse and so are the use cases to exploit it. This poses significant challenges for developing successful commercial systems.

1plusX offers a software platform along with end-to-end solutions that allows customers, mainly coming from verticals such as media, publishing, e-commerce, telecommunication, finance, and advertising to develop globally competitive data-driven products. The competencies at 1plusX are quite unique - for Switzerland and even in a European context, bringing together a leadership team with extensive development and product experience from companies like Google, Yahoo!, Linkedin, SpaceX, and Swisscom, as well as highly successful serial entrepreneurs (e.g. Scout24 group, Recommind). The technical team exclusively consists of graduates from top universities, a large majority being graduates (Master, PhD) from ETH Zurich. The mission of the company is to offer enterprise software solutions "Made in Europe/Switzerland" and to take into account the specific needs of companies vis-a-vis a global, largely US-dominated competition. A famous quote attributed to John Wanamaker, a department store owner is "Half the money spent on advertising is wasted, the trouble is we do not know which half". To address this, 1plusX aims at raising the quality and efficiency of user interactions by adapting and optimizing at the level of target groups and individuals.

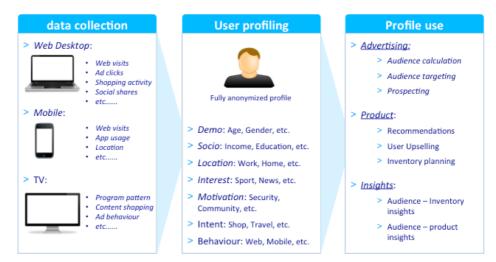
Current product. As a first step, 1plusX has developed a Semantic Data Management Platform (DMP) which is sketched below.



Data of different modalities are collected from multiple sources and then semantically enriched with data assets that relate observed behaviors to interpretable user traits. The latter include socio-demographics, interests, and intent as well as psychological factors. This way one can infer user traits in the process of computing user profiles, which is the algorithmic core of the semantic DMP. For example, based on the history of sites visited and/or product purchased, 1plusX's semantic DMP can infer gender, age group, education level, interest categories or preferred communication styles of a user. These inferred traits are "probabilistic" and are further qualified by the degree of confidence in the predicted user traits. Based on these inferred traits one can automatically map users to client-defined target groups. In addition, uninterpreted traits are identified via deep profiling. These attributes capture statistical regularities in the behavior of users that influence prediction of future needs and likely behaviors. They can also be used in forecasting for user populations. At the top, various modules support use cases from user analytics and business intelligence to individualized targeting or content-delivery. There are APIs (application programming interfaces) for a real-time integration of

¹ These details should be entered by the Implementation partner.

profiles and predictions, for instance, into real-time marketplaces as well as content or ad servers. A more use-case oriented view of 1plusX's offering is provided in the figure below.



Market and Competitors. 1plusX is positioned in the market for big data applications, specifically serving customers with a strong focus on digital advertisin, which includes publishers, advertisers, or digital media agencies. The market environment in which 1plusX is operating is highly favourable. Globally data volumes have been growing into the zetabyte range, a trend that is expected to persist [Fro14]. In lockstep with this growth in data volume, the adoption of big data applications is growing, too, with a forecasted market volume of approx. USD 123 billion by 2025, up from USD 47 billion in 2015. This translates to a 10% annual growth rate between 2015 and 2025. Consequently, 1plusX's customers are continuously allocating more of their marketing budget to digital advertising channels, which drives the need for technology solutions to manage and optimize digital advertising spend. The global share of digital advertising is projected to reach USD 253 billion by 2018, which accounts for 37% of all media spend [Woo15]. Within the digital advertising space, more and more budgets are being allocated "programmatically", i.e. subjected to a set of rules and algorithms, which again drives the demand for 1plusX's offering. Just the global programmatic display advertising spend is projected to grow by 36% annually from USD 4.5 bilion in 2013 to USD 20.8 billion in 2017 [Woo14].

A data management platform (DMP) addresses the task of integrating data from various sources, processing it and making the result available to use on advertising platforms such as Google's DoubleClick AdExchange. Industry leaders include Bluekai (acquired by Orcale in 2014 for USD 350-400 million [Ade14]), Adobe AudienceManager (part of the Adobe Marketing Cloud), Krux and Lotame. These companies have a strong market position in the United States (all being US-based) and many established partnerships with third-party data providers, as well as an array of integrations with other solutions in the digital advertising ecosystem. While these are offerings 1plusX currently cannot match, 1plusX has three distinct unique selling propositions. First, as a Switzerland-based company, 1plusX can tailor its product to European publishers, advertisers, and digital media agencies by working together with local data providers and understanding the needs of European companies. Second, a data privacy setup in accordance with strict Swiss/EU legislation and the Safe Harbor Agreement. Third, and most importantly, 1plusX offers globally unique, bleeding edge technology for user modeling and user analytics. As the use of software platforms like 1plusX's semantic DMP is often driven by quantitative success metrics such as user engagement, cost per click, etc., such technology is more then a "nice to have", but often offers an immediate return on investment for our customers.

At the other end of the spectrum of software solutions is a large number of platforms and libraries that support Big Data application in generic ways. This includes the basic **Hadoop stack**, various noSQL databases (e.g. MongoDB and Cassandra), systems like Spark or Flink and extensions built around it, as well as a number of other components developed under the umbrella of the Apache foundation and by cloud service providers. There are also various libraries and frameworks geared towards machine learning such as Tensor Flow (Google), scikit-learn, BigML or GraphLab (now Dato) to name just a few. The availability of these systems and components has enabled many massive data applications in industry that - for all practical reasons - would have been impossible to realize from scratch.

Customer needs. During the first year of 1plusX's existence, talks to current and future customers have surfaced a common industry need: The ability for the customer's own data scientists to flexibly model and explore their own data together with the additional data sources that 1plusX provides. We believe, and have been supported in this view by our customers, that neither the previously mentioned DMPs nor the general-purpose Big Data frameworks address this requirement appropriately, as explained in the following.

Most off-the-shelf DMPs offer very little support for companies to develop their own tailor-made solutions. Such systems are at best "configurable" in that they can combine different data sources in pre-defined ways or offer some logic for user id synching, user grouping into audiences, or exporting into other systems (e.g. advertising platforms). Current DMPs are *data* platforms, but *per se* are not *modeling* or *compute* platforms; this is a shortcoming that poses severe limitations on how such systems can be used.

Whereas current DMPs offer too little flexibility, the opposite is true for general-purpose Big Data frameworks. We saw several examples where companies struggled with the following challenges: (i) The required technical know-how to build solutions is high. Thus companies have to recruit scarce talents and build up sizeable teams just to run and maintain the basic infrastructure. (ii) While everything reads good on paper, actually integrating across a heterogeneous stack of systems and components is complex and often tricky and errorprone. (iii) This area is extremely fast-paced and constant investments are necessary to keep up with changing best practices and to take advantage of the best-in-breed systems. (iv) The wealth of possibilities and options is huge, but how to actually design and build an end-to-end system that can deliver business value is often non-trivial.

In order to properly address customer needs, we believe that what is crucially missing is a **programmatic platform** that enables custom-made functionality and solutions on top of it. Hence, this is where the focus of this project lies.

Project goal. The current 1plusX semantic DMP partially addresses the above challenges, but currently the data modeling is happening in a relatively rigid manner. The goal of this project is to expand the capabilities of the current offering by significantly improving the **deep profiling** aspects (see Figure 1) and by offering a flexible modelling layer on top. We propose to build a development platform that refrains from being generic and general-purpose, yet that exploits specific features and characteristics of user data and textual content, the emphasis being on preserving semantics and context. Our envisioned platform tightly integrates different modules, but not in a loosely-coupled service-based architecture. Rather we propose to support customers to specify joint models that more directly combine different data sources and preserve richer contextual information.

Following a recent "mega-trend" in machine learning, we believe that deep neural networks - equipped and augmented with probabilistic semantics where needed - are the prime choice for such a fundamental modeling language. One reason is that this family of models is supported by powerful and scalable computational frameworks such as Google's TensorFlow. We can thus fully-automatically learn and use deep models for cluster-scale computing, which alleviates the need to implement any special-purpose solution. Second, deep network models have shown enormous practical success and already revolutionized areas like machine vision, speech recognition and, most importantly for our goals, natural language understanding. The multibillion dollar investments that global Internet companies regularly make in this area also speaks volumes about its commercial importance.

The platform's aim is to cover the complete lifecycle of user interaction modeling. From the previously described specification of the model, a deep neural network is trained on all available data sources. The resulting recommendations or predictions are then evaluated either on available ground truth data, or in an A/B testing mode on live traffic (redirecting a part of the user interactions to the new engine and comparing with the current one). Finally, the platform deploys the newly trained model to production with the ease of a single click of a button.

Impact. While we think that this project is very ambitious and novel from a scientific and industry standpoint, one can foresee an even bigger commercial impact for Europe, and for Switzerland in particular. With the online advertising market – and, in fact, the whole online market – being controlled by U.S. companies (maybe with the exception of uprising Chinese competitors such as Baidu, Alibaba and Tencent), **Europe falls more and more behind**. With the recent ruling on the Safe Harbor agreement, it is not even clear whether European companies will be provided with all services by American companies in the future, as they might require data to be transferred to their data centers in the U.S.

Considering this situation, it is of high importance that Europe starts closing the gap that has opened in recent years. We believe that we are primed to contribute to this strategic goal, with a management team that has extensive work experience in some of the leading U.S. companies mentioned before, most notably Google. With this business and technological background, and being validated by talking to 1plusX's customers, we are convinced that significant improvements upon the current state of the art can be achieved. More precisely, optimal use of data requires that solutions are adapted to a company's specific use case. Enabling customers to develop these solutions themselves by providing effective tools provides the highest leverage in the current situation.

In case of a success of this project, competition in the online advertising market would be re-ignited, which would certainly be an improvement from the current quasi-monopolies. We also see this platform as an enabler for new ideas and even businesses to build upon. If data from several domains can be combined into a unified model of user interactions, one can imagine **completely new applications**. Areas that will benefit the most from this technology are those, where it is vital to understand the user's intentions in order to provide the adequate response. Typical use cases include receiving information (newspapers and videos), troubleshooting (help manuals), finding directions in the physical (maps) as well as the online world (search engine), providing the right tempo and individualized approach for learning (educational apps, e.g. for learning a new language), or making services more accessible for elderly or disabled people. All of these applications significantly improve with a better understanding of the user.

Example use case 1: Content recommendation. We illustrate the use of deep neural networks with the example use case of a publisher who wants to personalize the content of their news sites by recommending articles to users, based on their previous activity. To this end, a crawler would visit the publisher's website and extract the articles' content. This would constitute our primary data source. The extracted text would then be mapped into a high-dimensional semantic vector space with the help of a pre-trained neural network. In this vector space, documents that are semantically close – i.e. talk about the same ideas and concepts – are also spatially close. Even more interesting, users can also be mapped to this same space based on the articles they have previously read or the pages they have visited in the past. By performing a neighborhood search on the user (to simplify matters for the sake of explanation), one can discover articles of interest for the user, which the publisher can then recommend for reading.

Example use case 2: Custom interaction modeling for SMEs. A custom sports clothing company would like to get more insights into their users' behavior on its own website, as well as attract new users through advertising. The company has 10 employees and operates a website with its product as well as a web shop. By entering the 1plusX modeling platform, it can integrate its own data into 1plusX's pre-trained neural network, thereby leveraging the larger pool of data on online clothes shopping already in the 1plusX ecosystem. On the one hand, this allows the sports clothing company to better understand user behavior on their website. On the other hand, 1plusX can offer programmatic advertising through its partners (by directly exporting the specified and trained model from the platform to those partners) to enhance the clothing company's reach.

Example use case 3: Online/offline integration. One of the key offerings of a successful DMP product is online-offline integration. A soft drink company that launches a new product advertises on various media properties in the country. The targeting from the campaign is optimized by 1plusX's audience platform which analyses the CRM data of the soft drink company along with potential billing data from supermarket chains like Migros and Coop. Where available, the demographics of the customers (for instance, through loyalty cards program like Cumulus cards and Coop cards) are also included in the audience creation task. The campaign is tracked by 1plusX's servers and a detailed report is prepared on the reach of the campaign that includes the demographics of the users (age, gender, location, etc.). After the campaign is finished, CRM data is again matched with the reach of the campaign to measure the effectiveness of the campaign.

Business model and licensing. The business model of 1plusX is built around the core value proposition of user profiling and predictive user analytics. Customers are charged on a monthly basis (software license) depending on the number of user profiles 1plusX calculates for them (in million) and on the depth of the delivered features. Possible features are interfaces to other systems and additional user profile segments (e.g. psychometrics or buying intent). In addition, 1plusX offers consulting services to its customers, in particular technical consulting such as identifying the best ways to integrate 1plusX into the technology stack of the customer, or business consulting such as identifying the most promising use cases for 1plusX technology. The outcome of this project has a direct and significant impact on the core product of 1plusX and hence on the business model. Concretely, this benefits 1plusX in the following ways: (1) The much requested feature to flexibly model the customer's data (see "Customer needs") brings a competitive advantage for 1plusX, which we estimate to lead to an additional relative market share of 5 - 10% over the first three years. (2) The higher data quality that shall be achieved in this project will also lead to an increased data use of existing customers, which in turn will make it easier to acquire new customers, as more evidence for the quality of the platform can be collected. Most platforms suffer from a chicken-and-egg problem at the beginning, but once the platform reaches critical mass, the first few success stories almost automatically attract new customers. (3) New customer segments become accessible for 1plusX's data management and audience analytics technology. We primarily think of customers that were previously unable to combine signals from two different types of user interaction, such as online shopping and reading articles. Example use case 3 (online/offline integration) seems also very promising in that regard. (4) The platform can serve as a kind of data trading market for models that have been trained on data provided by 1plusX's other customers. While this might not be so enticing for private businesses, for whom data is a primary asset of their company's value, we see a lot of potential for current proponents of "open data", e.g. research or state and city governments.

We estimate the commercial impact of (1) to (3) in the first three years after completion of the project as follows:

Year	Goal	Min	Max
2018	3 customers (CHF 100'000 each)	CHF 300'000	CHF 1'000'000
2019	5-7 customers (CHF 50'000 to 150'000)	CHF 750'000	CHF 2'500'000
2020	10-20 customers CHF (50'000 to 200'000)	CHF 1'500'000	CHF 4'500'000

For (4), experience will show whether companies are willing to share models generated with their data, which is why we do not include the potential revenue in our forecast. As the provider and operator of the platform, 1 plus X would use a similar monetization model as Apple uses for its App Store, i.e. keep 30% of the profit to itself. The prices can either be set by 1 plus X according to some metric (number of events, number of users) or the market could be left to itself, and data buyers and sellers would negotiate the transaction price independently.

Commercial goals and deliverables.

- Run and use the platform internally for data sources owned by 1plusX and with Swiss websites as the scope.
- Run a pilot phase with a customer for the modeling platform.
- Convert the pilot customer to continue with the productionized platform.
- Convince two additional customers to use the productionized platform in the first year after completion
 of the project.

References.

[Ade14] Ad Exchanger, 2014, http://adexchanger.com/data-exchanges/oracle-to-buy-bluekai-for-estimated-400m-deal-presents-big-challenges/

[Fro14] Frost & Sullivan, 2014, Fast-Forward to 2025: Global Mega Trends and Implications of the Future World, http://www.slideshare.net/FrostandSullivan/top-global-mega-trends-and-implications-to-future-lives [Woo14] Woodside Capital Partners, 2014, Digital Ad Tech: Growth, Disruption, and Consolidation, http://www.woodsidecap.com/wp-content/uploads/2014/08/WCP-Ad-Tech-Report-20140821.pdf [Woo15] Woodside Capital Partners, 2015, Global Technology M&A Trends and Analysis, http://www.woodsidecap.com/wp-content/uploads/2015/07/WCP-Global-Technology-MA-Report-Final.pdf

2. What are the scientific and technological objectives and deliverables of this project?

Recent advances. Deep learning is a quantum leap in machine learning and data science. In a few years (since approx. 2013) it has revolutionized areas like speech recognition, computer vision, robotics, and natural language understanding, sweeping away existing approaches and paradigms. The current speed of innovation is unparalleled and the implications towards advancing machine intelligence are far-reaching. We want to make use of this scientific breakthrough in an area that is ripe for further innovation, namely predictive user analytics, in particular with data arising from interactions of users with semantically rich content (e.g. documents, articles, websites, emails, videos/TV, advertisement, etc.). As a starting point, we take the seminal work of Mikolov et al. [Mik13a], which is often referred to as word2vec. Here, symbols such as words are mapped to a (latent) vector representation, also called an embedding, in a way that words with similar meanings are mapped to nearby points. Note that this can be done - important for a country like Switzerland in a multilingual fashion. In addition, it has been shown (e.g. [Mik13b]) that one can perform simple vector arithmetics on word meanings, e.g. v King - v Man + v Woman ≈ v Queen, where "v word" denotes the word vector of the corresponding word. This line of research has been further advanced in many ways. Most notably, one can embed whole documents in a similar manner (doc2vec, cf. [Le14]) and there are now also embedding models for whole sentences that have shown impressive results in machine translation, e.g. [Sut14], as well as conversational agents, e.g. [Vin15]. We will now state our scientific contributions.

Deep neural networks. While semantic vector representations are typically extracted from text, we propose to co-embed text data with user interaction data. What this means is that we not only infer representations for language symbols (words, sentences, documents), but also - in complete analogy - for user actions and behaviors (events, browsing sessions, interests). This will be possible, whenever the basic user interactions deals with content that can itself be related to text as is often the case in an online environment, most notably for web page visits, where we can characterize the visited pages by their text content. This idea of embedding multiple data sources is not new. For instance, co-embedding images with text has led to the development of systems that can fully-automatically generate verbal descriptions of visual scenes at surprising accuracy (e.g. [Vin15]). It is clear that other modalities can also be co-embedded, e.g. media content or locations. In general, this will allow us to retain a lot more semantic and contextual information from the observed interactions of users with content. A naive version of the above is at the heart of methods for recommender systems, like the most successful approaches that have won the Netflix challenge (restricted Boltzmann machine, matrix factorization). Here users and items (such as movies) are embedded in a common space and user ratings are predicted based on the closeness of users and items in this representation. Our platform takes this simple, yet successful principle and extends it significantly for semantic user modeling, taking advantage of the additional benefits of deep learning.

Interpretability. A high-dimensional vector space might be a convenient representation of concepts for machines, but for humans this is typically not the case. For humans, characterizing an individual in terms of socio-demographics, interests and psychometrics (see Figure 1) is a lot more intuitive and helpful. When giving recommendations, especially for content, users will want to know why a certain article has been recommended to them. Therefore, one scientific objective of our project is to make the abstract semantic vectors meaningful to non-experts. Previous work by Zeiler et al. [Zei10, Zei11] has shown that a straightforward way to extract information from a trained neural network is to adjust the input to the neural network until one of the dimensions of the vector space is maximized (by triggering activations of the neurons in the output – or any intermediate – layer). By looking at the so-generated input, we can then visualize what abstractions the neural network has learned. This lead to surprising results when Google trained a neural network on YouTube videos and discovered that one dimension learned to identify cats [Le12].

We do not intend to identify cats. Nevertheless will we use these techniques to make our learned models human-interpretable, possibly discovering unforeseen correlations in user reading behavior. Concretely, we will use panel data (e.g. Amazon's Alexa, SimilarWeb, Link Institiute, NetMetrix or similar panel data providers) to be able to connect user embeddings with interpretable user traits such as socio-demographics, interests, etc. This will allow us to expand and multiply the value of panel data by propagating information across different modalities. It will make embeddings interpretable in terms of user traits that are commonly used for advertising and personalization.

Modeling platform. When building a platform for modeling user interaction data, one must first define a language for specifying these models. This definition can be divided into two steps. First, one has to identify the operations that one wishes to provide, and second, a way to perform these operations has to be declared. The former involves finding the right abstractions in our problem domain. The design space for the latter task reaches from creating a domain-specific language on one end, over exposing parameterized functions via a library or a public API, to an extensive configuration of an otherwise immutable executable program. After some initial investigation on the current state of the art, for a first version we decided to employ a library solution, which allows us to abstract away unnecessary (for our problem domain) complexity of the underlying

execution framework, and still allow the users to be flexible and write a program specifically for their needs. We are encouraged in this decision by similar solutions in popular research frameworks in the same field, like Caffe and Torch (see Section 3b).

The library will mainly be responsible for defining the model and everything around the model's life cycle management. This includes importing data from heterogeneous data sources, defining input, output, and the latent representations in between. It involves training a model and evaluating it, then adjusting its parameters to better match the desired result. Finally, the model's final version can be deployed to production. We believe that a library is capable of significantly simplifying these tasks for the users.

In the long term, we can also imagine to extend this library further into a simple domain-specific language. At the moment, there is an effort in the research community to specify languages for formulating the probabilistic properties of a problem to then infer the parameters of the model (and even the model itself). These languages are called probabilistic programming languages. Notably, the Probabilistic Computing Project at MIT has developed the probabilistic programming platform Venture [Man14], which aspires to overcome the major drawback of other approaches; scalability. While we think this is an interesting approach, we believe that the generality that current research in the field strives for will prevent an optimized solution for use cases that involve extremely large amounts of data, such as online user behaviors. We therefore intend to translate operations in our library into executions on Google's TensorFlow framework (www.tensorflow.org). TensorFlow has proven to exploit available computation power exceptionally well, and was designed for use with deep neural networks (although it allows computations of all models that can be expressed as a data flow graph). Building upon this product allows us to focus on our core innovation – defining the right abstractions for user interaction modeling – and get scalability for free.

Privacy. We look at several common practices in the online advertising industry with a critical eye. One specific behavior seems to be shared by most – if not all – players in the market: "Collecting more data is better, you never know when you might need it." This leads companies into judicial gray areas, and, as has unfortunately been the case repeatedly, even across the boundaries of the law [Ant11, vHo12]. We believe in a different approach to deliver relevant content to users by purposefully collecting specific data that we know can be conveniently ingested by our neural network. By extracting better signals, we can achieve better predictions with less data. This especially benefits small and medium enterprises, who might not have the vast streams of user data as the like of Google and Facebook.

There is an additional benefit to encoding incoming data directly into a model on which all further computations are performed: The raw data can be discarded shortly after its acquisition. Especially in advertising, where a buying intent usually exists between a few hours (e.g. commodities) to a few weeks (e.g. holidays), we do not feel that keeping months or years of data results in any tangible benefit for the user. We see our approach as particularly suited to address this concern.

On this note, we would like to mention that 1plusX respects a user's choice not to receive personalized content or advertisement. By either setting the DoNotTrack header in their browser, or opting out over a site designed to express user choice for online advertising (www.youronlinechoices.eu), users can prevent 1plusX from collecting data in the first place. In case data is being collected, a user is internally represented by an anonymous user id linking the data to a cookie set in their browser. By deleting the 1plusX cookie, users can irrevocably remove this link, making it impossible to reestablish a connection between the data and their browser. 1plusX is also in the process of acquiring certification with the European Interactive Digital Advertising Alliance (EDAA, www.edaa.eu).

Deliverables. We quickly give an overview of the deliverables that arise from our scientific and technological objectives:

- A semantic modeling platform prototype for working with user interaction data. This will be our main technological deliverable in the project and will also be used in our customer pilot.
- A word/sentence/document embedding model for all major Swiss languages plus English, based on
 pre-trained data (where available) and based on crawls of respective Web pages relevant to Swiss
 Web users. We will implement this on top of TensorFlow, a recently released open-source library by
 Google for deep learning. This will be part of the platform prototype and should have a simple
 interface to map text (words, phrases, sentences, documents) to a semantic vector representation.
- Co-embedding of anonymized user data from commercial 3rd party data providers (e.g. AddThis, Tell), which are already offered on the market. These data are (in part) already available to 1plusX as part of customer and license agreements. Besides being a central part of our platform prototype, we also wish to produce an evaluation of the quality of this co-embedding in the form of a report and possibly a scientific publication.

- Use of panel data to connect user embeddings with interpretable user traits (e.g. socio-demographics, interests). The platform prototype will support a simple user profile look-up, where an (anonymous) user ID is used as a lookup key to retrieve the corresponding user traits.
- A specification of the interface to the platform prototype, be it a domain-specific language implementation, a library, REST API, or something else. The specification shall be in a suitable format for the choice resulting from the investigation around the platform modeling language.

References.

[Ant11] Anthony, 2011, AOL, Spotify, GigaOm, Etsy, KISSmetrics sued over undeletable tracking cookies, http://www.extremetech.com/internet/91966-aol-spotify-gigaom-etsy-kissmetrics-sued-over-undeletable-tracking-cookies

[Le12] Le, Quoc V. "Building high-level features using large scale unsupervised learning." *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on.* IEEE, 2013.

[Le14] Le, Quoc V., and Tomas Mikolov. "Distributed representations of sentences and documents." *arXiv* preprint arXiv:1405.4053 (2014).

[Man14] Mansinghka, Vikash, Daniel Selsam, and Yura Perov. "Venture: a higher-order probabilistic programming platform with programmable inference." arXiv preprint arXiv:1404.0099 (2014).

[Mik13a] Mikolov, Tomas, et al. "Efficient estimation of word representations in vector space." arXiv preprint arXiv:1301.3781 (2013).

[Mik13b] Mikolov, Tomas, Wen-tau Yih, and Geoffrey Zweig. "Linguistic Regularities in Continuous Space Word Representations." *HLT-NAACL*. 2013.

[Sut14] Sutskever, Ilya, Oriol Vinyals, and Quoc VV Le. "Sequence to sequence learning with neural networks." *Advances in neural information processing systems*. 2014.

[vHo12] von Hoffman, 2012, Google Sued for Violating Apple Browser Privacy Protection,

http://www.cio.com/article/2371631/security0/google-sued-for-violating-apple-browser-privacy-protection.html [Vin15] Vinyals, Oriol, and Quoc Le. "A neural conversational model." *arXiv preprint arXiv:1506.05869* (2015). [Zei10] Zeiler, Matthew D., et al. "Deconvolutional networks." *Computer Vision and Pattern Recognition* (CVPR), 2010 IEEE Conference on. IEEE, 2010.

[Zei11] Zeiler, Matthew D., Graham W. Taylor, and Rob Fergus. "Adaptive deconvolutional networks for mid and high level feature learning." *Computer Vision (ICCV)*, 2011 IEEE International Conference on. IEEE, 2011.

- 3. What is the innovation content of the proposed project with regard to a) the current state of the partners' own research and development, b) the current state of national and international state of the art and c) the market and competitors? Have searches/surveys been performed (details of sources etc.)?
- a) This project aims to build a completely new modeling platform that has not been built before, neither by us nor our competitors. It can, however, make use of already existing components built at 1plusX, such as a web crawler that visits websites and extracts their text content. Regarding previous work with neural networks, 1plusX is currently exploring the word2vec technology [Mik13] for extracting user interests from reading behavior. The scientific staff at the data analytics laboratory at ETH is working on several projects involving deep neural networks, including sentence embeddings, entity linking, summarization and conversational agents.
- b) As computer science is a very international field, we directly compare our project to the international standards. In the following, we summarize related work in the two major areas of this project embeddings with deep neural networks and building a semantic modeling platform and at the end outline how we want to advance the current state of the art.

Deep neural networks. Deep learning is the popular term associated with the technique of using neural networks with multiple hidden layers to learn useful features or representation of the input data [Ben12] in an unsupervised fashion. For an easily accessible popular science introduction to deep learning, the reader is referred to [New12], [Pop15], or [Wir13].

Before 2006, deep learning had been studied for over 30 years but without much practical success due the computational and numerical precision issues involved in training deep neural networks. However with the advent of greedy layerwise unsupervised pre-training [Hin06], the field had a revival and massive success in many different areas of machine learning and pattern recognition. The popular models of deep learning now use either a deep belief network (DBN) structure or a convolutional neural network (CNN) structure.

In the field of computer vision, deep learning algorithms improved the existing state of the art performances by orders of magnitude on handwriting recognition tasks [Cir12, Rif11], and object detection in natural images [Kri12, Le12, Sze14, Sim14]. In the field of speech recognition and signal processing, both academic and industrial research labs have extensively used deep learning to improve performance on speech recognition tasks [Dah12, Hin12, Sei11]. Polyphonic transcription [Bou12] and music information retrieval [Ham11] are other example areas in signal processing revolutionized by deep learning techniques.

The application area of crucial importance to our research is natural language processing (NLP). Word embeddings that produce a distributed representation of words have been demonstrated to be vastly superior to traditional handcrafted language models in many of the language processing tasks. SENNA [Col11a] and word2vec/doc2vec [Mik13, Le14] are examples of deep representational learning of words, sentences and documents. Sentiment analysis, which is a powerful tool for our business in order to quantify intent and user satisfaction, is another area of NLP where deep learning vastly outperforms traditional approaches [Glo11]. Due to the nature and location of 1plusX's business, machine translation is an important area in order to seamlessly translate between the different European languages. Here again, deep learning produces state of the art results in effective language translation [Kle12, Kal13, Sut14].

Another key research area that is directly applicable to our research problems is transfer learning, which deals with the transfer of learned knowledge or representations across different learning tasks. In many applications demonstrating the power of deep learning, researchers have successfully combined NLP and image understanding [Kar15] to produce descriptions of objects in images and also produce running text summaries and stories from images. The researchers have embedded both text and images into the same vector space. These results have basically inspired our project, in which we aim to – for the first time – co-embed text and users, and expect a similar success.

Modeling platform. Currently, several neural network frameworks are in use in industry and the scientific community. Very recently, Google has open-sourced it's machine learning library [Goo15] developed and used internally by the Google Brain team to perform research with deep neural networks, called TensorFlow (www.tensorflow.org). It allows for quick prototyping as well as running a system in production, and can intelligently distribute computation to compute units in heterogeneous hardware setups. It promises to meet our demands regarding flexibility and scalability for our deep neural networks platform, and we intend to build our system upon it. Previously, Google has conducted neural network research on its DistBelief framework [Dea12] which also achieved high scalability, but supported a smaller set of models that it was able to express. The research community in deep learning has mainly settled on three frameworks: Caffe, Theano and Torch. Caffe [Jia14] is a deep learning framework for quick training of convolutional nets developed at UC Berkeley. Theano [Ber10] is able to define, optimize, and evaluate mathematical expressions involving multi-dimensional

arrays efficiently. Finally, Torch [Col11b] is a suite of deep learning algorithms, used by Google DeepMind, Twitter, IBM, Yandex, and Facebook, who also contributed functionality to the framework. As explained previously, we will build upon TensorFlow and enhance its functionality for user behavior modeling. We believe that TensorFlow is the right choice due to our requirements regarding flexibility and scalability, which have both been a central concern in building this framework.

c) **Market and competitors.** In section 1, we have described the discrepancies between the current state of the art in the industry and the requests from our customers. Current solutions either constrain customers too much (current DMPs), thereby not letting them model solutions in their specific problem domains, or leave the customers with too much freedom (general-purpose Big Data frameworks) requiring large upfront investments in team and technology as well as difficulties when integrating across heterogeneous systems. We believe that our semantic platform will find the sweet spot between leaving enough freedom to create models for specific problem domains, and providing enough guidance and integration with other systems to enable rapid development and testing of new models. By combining it with the neural networks, which have proven very successful in similar areas, we aspire to set a new industry standard for modeling user interaction data.

3.1 Has preliminary work already been undertaken? If so: give a short summary.?²

The current semantic DMP at 1plusX implements a simpler matrix factorization method that can be seen as a simple precursor to what we intent to do. This system is in production with a number of clients, supporting 10M+ unique user IDs and 50M+ events per day. This work has been conducted in the context of two master projects that have established a collaboration between the partners of this proposal.

Prof. Hofmann has been working on semantic data modeling for almost 20 years. He is the inventor of topic models, also known as probabilistic latent semantic analysis ([Hof99a, Hof99b, Hof01, Hof04: these papers have been cited about 10000 times in total). Specifically the work on recommender systems (Hof04, Bas04) is highly relevant for the proposed research. He has also conducted work in this area in the 8 years he was Engineering Director at Google (2005-2012, confidential and undisclosed). His research group at ETH is currently conducting research on embedding models and deep networks to use in the context of entity linking as well as text compositionality.

Dr. Vanchinathan has recently completed a Ph.D. Thesis that deals with Bayesian optimization techniques that are especially useful for learning in a setting, where user interaction can be actively managed. His work on online recommendations and inference techniques from partial feedback will be particularly useful for this project. We expect to further benefit from these insights and results.

3.2. What human and material resources are available to the project partners? (e.g. available research staff, equipment, etc.)

A dedicated scientific staff at the Data Analytics Laboratory at ETH can be consulted to help with scientific questions. Furthermore, the Max Planck ETH Center for Learning Systems, co-founded recently by Thomas Hofmann, holds a large pool of PostDocs and PhD students which could also be involved if need be.

1plusX will provide R&D resources with employees holding a PhD or Master degree in Computer Science. They will deal with all aspects of implementation and productionization of the platform. They will also help to gather the relevant data sources. For various tasks like, for example, crawling web pages or extracting information from websites, 1plusX has already built Software components that can be utilised in this project.

Moreover, 1plusX will make dedicated compute resources available, most likely in the form of cloud computing infrastructure.

3.3 How do you assess the impact of the project in terms of ecological sustainability?

For example as regards to

- Sustainable resource use (commodities, materials)
- Climate change mitigation (energy use, greenhouse gas emissions)
- Biodiversity and restoration of natural habitats (land and water)
- Prevention of pollution (waste, air pollution)

The project itself does not have a direct impact on ecological sustainability.

References.

[Bas04] Basilico, Justin, and Thomas Hofmann. "Unifying collaborative and content-based filtering." *Proceedings of the twenty-first international conference on Machine learning*. ACM, 2004.

² Important relevant publications should be enclosed with the application.

[Ben12] Bengio, Yoshua, Guillaume Alain, and Salah Rifai. "Implicit density estimation by local moment matching to sample from auto-encoders." *arXiv preprint arXiv:1207.0057* (2012).

[Ber10] Bergstra, James, et al. "Theano: a CPU and GPU math expression compiler." *Proceedings of the Python for scientific computing conference (SciPy)*. Vol. 4. 2010.

[Bou12] Boulanger-Lewandowski, Nicolas, Yoshua Bengio, and Pascal Vincent. "Modeling temporal dependencies in high-dimensional sequences: Application to polyphonic music generation and transcription." arXiv preprint arXiv:1206.6392 (2012).

[Cir12] Ciresan, Dan, Ueli Meier, and Jürgen Schmidhuber. "Multi-column deep neural networks for image classification." *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on.* IEEE, 2012. [Col11a] Collobert, Ronan, and J. Weston. "SENNA." *NEC Laboratories America, Inc*6 (2011).

[Col11b] Collobert, Ronan, Koray Kavukcuoglu, and Clément Farabet. "Torch7: A matlab-like environment for machine learning." *BigLearn, NIPS Workshop*. No. EPFL-CONF-192376. 2011.

[Dah12] Dahl, George E., et al. "Context-dependent pre-trained deep neural networks for large-vocabulary speech recognition." *Audio, Speech, and Language Processing, IEEE Transactions on* 20.1 (2012): 30-42. [Dea12] Dean, Jeffrey, et al. "Large scale distributed deep networks." *Advances in Neural Information Processing Systems*. 2012.

[Jia14] Jia, Yangqing, et al. "Caffe: Convolutional architecture for fast feature embedding." *Proceedings of the ACM International Conference on Multimedia*. ACM, 2014.

[Glo11] Glorot, Xavier, Antoine Bordes, and Yoshua Bengio. "Domain adaptation for large-scale sentiment classification: A deep learning approach." *Proceedings of the 28th International Conference on Machine Learning (ICML-11)*. 2011.

[Goo15] Google, 2015, https://googleblog.blogspot.ch/2015/11/tensorflow-smarter-machine-learning-for.html [Ham11] Hamel, Philippe, et al. "Temporal Pooling and Multiscale Learning for Automatic Annotation and Ranking of Music Audio." *ISMIR*. 2011.

[Hin06] Hinton, Geoffrey E., and Ruslan R. Salakhutdinov. "Reducing the dimensionality of data with neural networks." *Science* 313.5786 (2006): 504-507.

[Hin12] Hinton, Geoffrey, et al. "Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups." *Signal Processing Magazine, IEEE* 29.6 (2012): 82-97.

[Hof99a] Hofmann, Thomas. "Probabilistic latent semantic indexing." *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval.* ACM, 1999. [Hof99b] Hofmann, Thomas. "Probabilistic latent semantic analysis." *Proceedings of the Fifteenth conference on Uncertainty in artificial intelligence.* Morgan Kaufmann Publishers Inc., 1999.

[Hof01] Hofmann, Thomas. "Unsupervised learning by probabilistic latent semantic analysis." *Machine learning* 42.1-2 (2001): 177-196.

[Hof04] Hofmann, Thomas. "Latent semantic models for collaborative filtering." *ACM Transactions on Information Systems (TOIS)* 22.1 (2004): 89-115.

[Kal13] Kalchbrenner, Nal, and Phil Blunsom. "Recurrent Continuous Translation Models." *EMNLP*. 2013.

[Kar15] Karpathy, Andrej, and Li Fei-Fei. "Deep visual-semantic alignments for generating image descriptions." *arXiv preprint arXiv:1412.2306* (2014).

[Kle12] Klementiev, Alexandre, Ivan Titov, and Binod Bhattarai. "Inducing crosslingual distributed representations of words." (2012).

[Kri12] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

[Le12] Le, Quoc V. "Building high-level features using large scale unsupervised learning." Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on. IEEE, 2013.

[Le14] Le, Quoc V., and Tomas Mikolov. "Distributed representations of sentences and documents." *arXiv* preprint arXiv:1405.4053 (2014).

[Mik13] Mikolov, Tomas, et al. "Efficient estimation of word representations in vector space." *arXiv preprint arXiv:1301.3781* (2013).

[New12] The New Yorker, 2012, Is "Deep Learning" a Revolution in Artificial Intelligence?, http://www.newyorker.com/news/news-desk/is-deep-learning-a-revolution-in-artificial-intelligence

[Pop15] Gershgorn, 2015, How Google Aims to Dominate AI, http://www.popsci.com/google-ai

[Rif11] Rifai, Salah, et al. "Contractive auto-encoders: Explicit invariance during feature

extraction." Proceedings of the 28th International Conference on Machine Learning (ICML-11). 2011.

[Wir13] Metz, Facebook's "Deep Learning" Guru Reveals the Future of AI,

http://www.wired.com/2013/12/facebook-yann-lecun-ga/

[Sei11] Seide, Frank, Gang Li, and Dong Yu. "Conversational Speech Transcription Using Context-Dependent Deep Neural Networks." *Interspeech*. 2011.

[Sim14] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).

[Sut 14] Sutskever, Ilya, Oriol Vinyals, and Quoc VV Le. "Sequence to sequence learning with neural networks." *Advances in neural information processing systems*. 2014.

[Sze14] Szegedy, Christian, et al. "Going deeper with convolutions." arXiv preprint arXiv:1409.4842 (2014).

4. Position of this project within your R&D activities

Topic	Funding agency	From to (years only)	
Торю	T diffullig agency	Trom to (years only)	
		,	
		,	
		,	
☐ Yes ☒ No If so, please specify:		another funding agency?	
If so, please specify:	eive financial support for this R&D sector?		
If so, please specify: B. Do you currently rec	eive financial support for this R&D sector? cify:		
If so, please specify: B. Do you currently rec	eive financial support for this R&D sector?	From to (Years only)	
If so, please specify: B. Do you currently rec. No Yes, please spec	eive financial support for this R&D sector? cify:		
If so, please specify: B. Do you currently rec. No Yes, please spec	eive financial support for this R&D sector? cify:	From to (Years only)	

5. Research and project plan

5.1. Planned, well defined problem solving strategy.

The project will be organized in modules further explained below. The research questions will be solved at ETH, while 1plusX takes care of productionization and further development that is necessary for the application to specific business use cases.

Team. The project team will consist of 1 PhD student at the ETH Data Analytics Laboratory who will carry out the research tasks and build a prototype of the modeling platform. At 1plusX, a project manager will coordinate the project, help with scientific questions and supervise week-to-week advances. Furthermore, a software engineer at 1plusX will integrate and extend research results into 1plusX's software stack. The programmer will also productionize the platform prototype towards the end of the project. The CTI funding will be used fully for research at ETH.

Dr. Hastagiri Vanchinathan will act as a project manager on 1plusX's side. At ETH, Prof. Thomas Hofmann will be responsible for the research part. The project partners have worked in a similar configuration before with very good success.

Modules. The project will be organized in modules, which correspond to the scientific and technological objectives:

Module A – Text embedding module: Using and extending models like word2vec and doc2vec, we form distributed respresentations of words, sentences/paragraphs and documents in the target languages. The input for the text module would be crawled webpages in the major Swiss languages (German, French and Italian) plus English that are publicly accessible on the Internet. As validation of the embeddings, we compare the models performance against state-of-the-art results on tasks like text classification, named entity recognition, summarization and sentiment analysis.

Module B — User embedding modeling: We want to co-embed users into the same space that we have embedded the text from Module A. As input, we would use anonymized web visits of users that are available to 1plusX via their own and partners' data collection, as well as from third party sources. Evaluation will certainly involve manual anecdotal analysis, next to a measure of the model's predictive power. To attain this score, we would let the model predict future web visits of a user, and then compare against a test set that was previously held out.

Module C – Interpretable user traits: Here, we want to make use of panel data to relate the user model trained in Module B to tangible user traits, which may be demographic, interests, psychometrics, or some other dimension that lets us capture properties of user interaction. As a nice benefit, this can also act as a validation of the co-embedding from Module B. It furthermore enables comparisons against known ground-truth data.

Module D – Modeling language definition: Our goal is to define a modeling language that can express the properties discovered in modules B and C, and then be able to map those instructions into executable operations on Google's TensorFlow framework. The language should allow customers to define users in the form of interpretable traits, and as (non-)similarity to other users, or even to specific content embeddings. It should also allow for incorporating known interactions between data sources.

Module E – Modeling platform prototype: We build a modeling platform that can be programmed with the language from module D. It should be usable by data scientists without a deep understanding of the underlying algorithms. Supported operations include defining and importing data from various data sources, specifying desired analytical computations based on the interpretable user traits from module C, evaluating the models and exporting the result.

Module F – Pilot and productionization: Working closely with a yet to be chosen customer, the modeling platform from Module 5 would be deployed for their use during a pilot phase. Feedback would be collected on the quality of the interface, modeling and performance. This feedback would then be integrated into the process of productionizing the modeling language and the platform itself.

Risk assessment.

Risk Consequences	Estimation	Preventive Action
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	I · · ·		
Module A: Our embeddings don't come	This would severely diminish the success	Low risk. Good results on several evaluation data	Through our contacts, we can involve experts that
within reach of state-of-	probability of subsequent	sets have been replicated	already have experience
the-art performance of	tasks building upon these	by many people for deep	on this task.
current systems. Module B: We cannot	embeddings. This is the core of our	neural networks. Low risk. As we have	If embedding users
reasonably co-embed	idea and would not allow	pointed out in section 3.1,	proves to be impossible,
users into the same	a meaningful continuation	similar co-embeddings	there is little that we can
space as text content.	of the project.	have already been done	do about it. This is the
		successfully.	main uncertainty in our
			project, and at the same
			time our major research question.
Module C: The user	The user modeling via	Medium Risk. While the	We could use the events
embeddings are not	traits and interests in the	embeddings offer a nice	directly as a predictor of
useful as predictors for	platform (Module E) will	representational link	socio-demographic traits
socio-demographic traits	be affected.	between users and	or interests.
or interests		events, we would lose some of the predictive	
		and inference	
		functionalities.	
Module D: No useful	This will reduce the	Low risk. A lot of the	A one-to-one
abstractions can be	innovation content of our	abstraction work has	correspondance to TensorFlow's
found to express computations on deep	modeling platform (Module E).	been taken from us by Google, who released	abstractions could be
networks.	(Wodale L).	TensorFlow as the	used.
		product of their second	
		iteration on working with	
Madula E. Tha platform is	The platforms has a second	deep networks.	Ma lanca anna ta
Module E: The platform is not expressive enough.	The platform becomes less valuable for	Medium risk. We believe that with the results from	We have access to senior systems designers
not expressive enough.	customers, as	modules A to C, we	from Google, who we
	expressiveness is what	should definitely have	could ask for guidance on
	we mainly went to	and and an annual incidents into	
1	we mainly want to	gained some insights into	this task.
	improve compared to	how to model users.	this task.
Module F: The production	improve compared to current solutions.	how to model users.	
Module F: The production platform is not performant	improve compared to	how to model users. Low risk. Since we intend	We consider removing
Module F: The production platform is not performant enough.	improve compared to current solutions. The platform becomes	how to model users.	
platform is not performant	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly	We consider removing
platform is not performant	improve compared to current solutions. The platform becomes less valuable for the customers who might	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability,	We consider removing
platform is not performant	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't	We consider removing
platform is not performant	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability,	We consider removing
platform is not performant enough. Module F: We don't find a	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently	We consider removing functionality. Contact other customers
platform is not performant enough. Module F: We don't find a customer to run the pilot	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer	We consider removing functionality. Contact other customers and inform them about
platform is not performant enough. Module F: We don't find a	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design of the platform from	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature,	We consider removing functionality. Contact other customers and inform them about our new feature (which
platform is not performant enough. Module F: We don't find a customer to run the pilot	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature, so we believe it will be	We consider removing functionality. Contact other customers and inform them about
platform is not performant enough. Module F: We don't find a customer to run the pilot with.	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design of the platform from Module E.	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature, so we believe it will be easy to start a pilot with them.	We consider removing functionality. Contact other customers and inform them about our new feature (which we will do anyways).
platform is not performant enough. Module F: We don't find a customer to run the pilot with. Module F: We don't finish	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design of the platform from Module E.	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature, so we believe it will be easy to start a pilot with them. High risk. The	We consider removing functionality. Contact other customers and inform them about our new feature (which we will do anyways). During development and
platform is not performant enough. Module F: We don't find a customer to run the pilot with.	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design of the platform from Module E. 1plusX has to finish on its own. No further funding	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature, so we believe it will be easy to start a pilot with them. High risk. The combination of a	We consider removing functionality. Contact other customers and inform them about our new feature (which we will do anyways). During development and productionization, current
platform is not performant enough. Module F: We don't find a customer to run the pilot with. Module F: We don't finish	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design of the platform from Module E.	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature, so we believe it will be easy to start a pilot with them. High risk. The combination of a research and a software	We consider removing functionality. Contact other customers and inform them about our new feature (which we will do anyways). During development and productionization, current progress is reevaluated
platform is not performant enough. Module F: We don't find a customer to run the pilot with. Module F: We don't finish	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design of the platform from Module E. 1plusX has to finish on its own. No further funding	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature, so we believe it will be easy to start a pilot with them. High risk. The combination of a	We consider removing functionality. Contact other customers and inform them about our new feature (which we will do anyways). During development and productionization, current
platform is not performant enough. Module F: We don't find a customer to run the pilot with. Module F: We don't finish	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design of the platform from Module E. 1plusX has to finish on its own. No further funding	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature, so we believe it will be easy to start a pilot with them. High risk. The combination of a research and a software project doesn't promise to be exactly on time, as both are notoriously hard	We consider removing functionality. Contact other customers and inform them about our new feature (which we will do anyways). During development and productionization, current progress is reevaluated and the timetable adjusted. In extreme cases, 1plusX could
platform is not performant enough. Module F: We don't find a customer to run the pilot with. Module F: We don't finish	improve compared to current solutions. The platform becomes less valuable for the customers who might prefer their in-house solutions. We don't receive feedback on the design of the platform from Module E. 1plusX has to finish on its own. No further funding	how to model users. Low risk. Since we intend to build upon Google's TensorFlow framework, which is explicitly designed for scalability, we believe that we won't run into performance problems. Low risk. We currently already have a customer interested in this feature, so we believe it will be easy to start a pilot with them. High risk. The combination of a research and a software project doesn't promise to be exactly on time, as	We consider removing functionality. Contact other customers and inform them about our new feature (which we will do anyways). During development and productionization, current progress is reevaluated and the timetable adjusted. In extreme

^{5.2.} Project plan with timetable, work packages as well as clearly defined and scheduled milestones (what can be verified, seen, measured etc. at what point in time?) and planned allocation of resources (definition of milestones and results to be achieved, bar chart to be included).

Module A

WP A.1 Data collection of webpages in the supported languages

Input: 2MM (1plusX)

Output: Repository of webpages as a result of the crawling pages for the four languages. Could also be augmented by Wikipedia language dumps and pre-trained word vectors from Google.

WP A.2 Creation of text embeddings

Input: 2MM (ETH)

Output: Trained word and document vectors. Embedding models across all target languages.

WP A.3 Validation of text embeddings

Input: 2MM (ETH)

Output: Performance numbers on standard text modeling and NLP tasks like classification, summarization,

etc. Comparison between the different language models.

Module B

WP B.1 Data collection of user web visits

Input: 2MM (1plusX)

Output: Anonymized browsing events from users who browse partner webpages.

WP B.2 Creation of user embeddings

Input: 2MM (ETH)

Output: Users are reprensented as embeddings in the same space as the webpages.

WP B.3 Validation of user embeddings

Input: 2MM (ETH)

Output: Summary of anecdotal analysis and predictive power evaluation.

Module C

WP C.1 Data collection of ground truth data

Input: 2MM (1plusX)

Output: Non-personally identifiable ground truth data for logged in users on partner websites.

WP C.2 Interpretable user traits based on user embeddings

Input: 3MM (ETH)

Output: Report about how a user embedding can be connected to understandable user traits.

Module D

WP D.1 Modeling Language

Input: 2MM (ETH)

Output: Specification of a representational language for the semantic modeling platform.

Module E

WP E.1 Implementation of platform prototype

Input: 6MM (ETH)

Output: A modeling platform based on the modeling language specification from Module D that has the following features:

- Import various data sources
- Specify user interactions/behaviors
- Train a model
- · Evaluate the model

Module F

WP F.1 Evaluation of prototype with pilot customer, integrating the feedback.

Input: 4MM (1plusX and ETH)

Output: Improvements to the user interface, as well as the handling and operation of the platform. Possibly discovery of new abstractions for user modeling.

WP F.2 Productionization of the platform prototype

Input: 4MM (1plusX)

Output: The modeling platform is optimized for computational speed and memory requirements. Finally, the platform is integrated into 1plusX's offering.

Milestones.

We now define the milestones that contain concrete deliverables for our project. The very first milestone is already the most important one, as it defines what can still be achieved in the rest of the project. In the worst case, we would have to abort the project if our results don't look promising at milestone 1.

M1 | Co-embedding of text and user behavior

At the time of milestone 1, we should have finished modules A and B. This should give us a clear understanding of how to answer our main research question, namely how user behaviors and text can be co-embedded. As our envisioned platform is a mere interface to specify models on this co-embedding, the continuation of the project would be fruitless without a promising direction from our investigations.

Deliverable: A report with our analysis from modules A and B. The report should clearly state in what direction the project aims to continue, or, in case of failure of module A/B, why the project is to be aborted.

M2 Interpretation of user traits from user/text co-embedding

At milestone 2, module C has finished. The results of this work package will tell us how the user modeling part of the language specification in module D will look like, so it is required to finish before the start of module D.

Deliverable: A report with the results of our analysis. This report should contain a summary of how the embedding of user behavior can be interpreted in terms of user traits. In case the embedding also gives hints about a user's demographic or interests, the report should contain an evaluation against ground-truth data.

M3 | Modeling language specification

At milestone 3, the specification for the modeling language should be completed. This is a requirement for the user interface of module E, and should already give some indication towards the general design of the modeling platform.

Deliverable: A specification of the modeling language.

M4 | Modeling platform prototype

A prototype of the platform should be finished at the time of milestone 4. This also marks the start of the pilot project with a customer of 1plusX, which cannot begin without the prototype. The system should be able to import various data sources, let the user specify a model, train that model and evaluate it. The goal for the prototype is to be functionally complete.

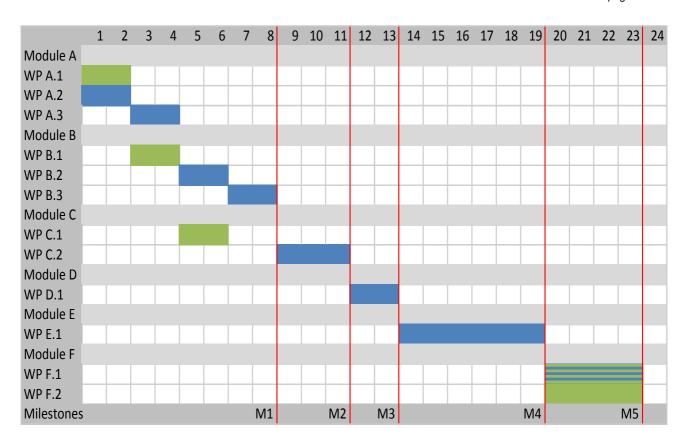
Deliverable: The platform prototype.

M5 | Production platform

The completion of the production platform also marks the end of our project. At this point in time, the platform should now also satisfy requirements regarding performance and intuitiveness of the user interface. The last month is left open as a buffer in case of delays.

Deliverable: None, the production platform will be used by 1plusX internally.

Timetable.



5.3. Project management and structure

Dr. Hastagiri Vanchinathan will manage the project at 1plusX, who will be responsible for overall project management. At ETH, Prof. Thomas Hofmann is responsible for the project.

The research assistant will meet weekly with the project manager and, if necessary, with the 1plusX team.

5.4.	Do you feel that the project results may give rise to a patent? ☐ Yes ☐ No
5.5.	Have all project partners reached a written agreement concerning patent rights as well as ownership and use of intellectual property resulting from the proposed CTI project?
	If so, please give a brief outline or a copy of the agreement:

If project partners have entered into an agreement on intellectual property rights and rights of use, or CTI asked for such an agreement, the signed agreement must be provided to the CTI before the grant funding contract may be issued.

5.6. Recapitulation of the project plan:

Please indicate the allocation of research tasks among the various partners

Description of R&D activities based on the project plan (work packages)	Research partner	%³ Share	Implementation partner	%³ Share	Outsourced to third party	%³ Share	
h dank a Kasa Sasa	parare	0.00	P	0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
		0.00		0.00		0.00	
	Subtotal	0.0		0.0		0.0	
	Total	must add up to 100%					

 $^{^{\}scriptsize 3}$ Expenditure of time as percentage of total

6. Financial Plan

Breakdown of total project costs into the following three categories:

- 6.1. Equipment costs (items of enduring value),
- 6.2. Other costs (consumables, miscellaneous expenses) and
- 6.3. Wage costs.

The individual costs should be itemised separately, by

- a) Costs to be covered by federal funds
- b) Costs incurred by implementation partners either in the form of cash contributions⁴ or other contributions according to art. 5 and 8 para. 5 of the CTI Funding Regulation (SR 420.124).

VAT: All funding contributions can be listed with VAT. The relevant costs must be factored into the requested funding amount under the relevant headings. If the request is subsequently approved, the costs will be paid along with the usual funding instalments. The VAT paid by the research partner must be appropriately documented in the final financial report.

6.1.a Equipment costs (after deduction of all discounts)

* CTI funding criteria only allows for payment of wages to researchers. Equipment and material may only be purchased with CTI funds in exceptional cases (Explanations must be provided in 6.1.b).

Item (incl. model and supplier)	Location during/ after project	* Federal/CTI share of costs in CHF	Cash contributions by impl. partner(s) ⁴ in CHF	Other contributions by impl. partner(s) in CHF	Total in CHF
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
	1	0	0	0	0
Total		0	0	0	0

6.1.b Which equipment (items of enduring value) purchased using federal funds may be reused after the project is completed?

By whom (e.g. higher education institution or company) and for what purpose?

6.2.a Other costs (consumables, miscellaneous expenses)

* CTI funding criteria only allows for payment of wages to researchers who work for non-profit organisations. Equipment and material may only be purchased with CTI funds in exceptional cases (Explanations must be provided in 6.2.b).

Use of funds	* Federal/CTI share of costs in CHF	Cash contributions ⁴ by impl. partner(s) in CHF	Other contributions by impl. partner(s) in CHF	Total in CHF
Acquisition of panel data	0	0	20000	20000
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
	0	0	0	0
Total	0	0	20000	20000

6.2.b Please explain why federal funding must be provided to cover equipment costs. (Expenses and consumables can not be covered by CTI funds)

⁴ Cash contributions to cover project costs incurred by research partner (VAT included).

6.3. Wage costs (net wage + employer/employee social insurance contributions = total wage costs per employee)
Wage levels: see Research and Innovation Promotion Ordinance RIPO of 10 June 1985 "Assessment of CTI funding for projects"
(Art. 63 RIPO of 29 November 2013 in conjunction with Art. 10s para. 7 including annex RIPO of 10 June 1985)

Please make sure to use the latest version of this form (www.kti.admin.ch).

Project function	Rate category A (Implementation partner/UAS)	Rate category B (Universities)	Rate category B+ (FIT Domain)
Project manager ! Important: There may only be 1 project manager for the entire project, up to a max. of 365 hours per year, additional hours shall be paid at the wage level for "experienced researchers".	CHF 148/h max.	CHF 105/h max.	CHF 119.70/h max.
Deputy project manager ! Important: There may only be 1 deputy project manager for the entire project, up to a max. of 365 hours per year, additional hours shall be paid at the wage level for "experienced researchers".	CHF 127/h max.	CHF 87/h max.	CHF 99.20/h max.
Experienced scientists	CHF 105/h max.	CHF 71/h max.	CHF 80.95/h max.
scientific assistants	CHF 84/h max.	CHF 60/h max.	CHF 68.40/h max.
Technicians, programmers	CHF 74/h max.	CHF 54/h max.	CHF 61.55/h max.

Project team members

*Required field

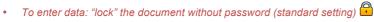
Please calculate time on project (hours) x hourly rate in CHF

								П					
* Surname	Marfurt			* First name	Andreas			sł	CTI nare of co	sts	Implem	ent. par of cost	rtner shar ts
* Year of birth	1989			Nationality	Swiss								
* Acad. level	MSc			since	2013								
* Qualification	Machine	e learning		since	2012								
*Research role in project	scientific	c assistant		* Ph.D. student	yes ⊠	no 🗆							
*Hourly rate in CHF	47			*Position in company	Research assistant	Research assistant							
* Employer	ETH Zü	rich		* Place of work	ETH Zürid	ch							
Wages covered by	1st pr	oject year	2nd	project year	3rd proj	ect year							
* Fed./CTI funding	CHF	87984	CHF	87984	CHF	0		CHF	175	968			
* Impl. partner	CHF	0	CHF	0	CHF	0					CHF		0
Subtotal	CHF	87984	CHF	87984	CHF	0							
* Time on project (hours)		1872 h		1872 h		0 h	1						
* Surname	Vanchir	nathan		* First name	Hastagiri	Prakash							
* Year of birth				Nationality									
* Acad. level	Dr.			since	2015								
* Qualification	Machine	e learning		since									
* Research role in project	Project i	manager (1)	()	* Ph.D. student	yes 🗆	no 🛚							
*Hourly rate in CHF	130			*Position in company	Team Software Engineeri	Lead ing							
* Employer	1plusX	AG		* Place of work	1plusX A	G							
Wages covered by	1st pr	oject year	2nd	project year	3rd proj	ect year							
* Fed./CTI funding	CHF	0	CHF	0	CHF	0		CHF		0			
* Impl. partner	CHF	47450	CHF	47450	CHF	0					CHF	94	4900
Subtotal	CHF	47450	CHF	47450	CHF	0							
* Time on project (hours)		365 h		365 h		0 h	١						

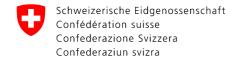
* Surname	Tschofen		* First name	Andreas	; 				
* Year of birth	1990		Nationality	Austria					
* Acad. level	MSc		since	2013					
* Qualification	Machine learning software enginee	/ ring	since	2011					
* Research role in project	Programmer		* Ph.D. student	yes □	no 🛚				
*Hourly rate in CHF	65		* Position in company	Software Enginee					
* Employer	1plusX AG		* Place of work	1plusX /	4G				
Wages covered by	1st project year	2nd	project year	3rd pro	oject year				
* Fed./CTI funding	CHF C	CHF	0	CHF	0	CHF _	0		
* Impl. partner	CHF 42250	CHF	42250	CHF	0			CHF	84500
Subtotal	CHF 42250	CHF	42250	CHF	0				
* Time on project (hours)	650	ו	650 h		0 h				
* Surname			* First name						
* Year of birth			Nationality						
* Acad. level			since						
* Qualification			since						
* Research role in project	please select		* Ph.D. student	yes □	no 🗆				
*Hourly rate in CHF	0.00		* Position in company						
* Employer			* Place of work						
Wages covered by	1st project year	2nd	project year	3rd pro	oject year				
* Fed./CTI funding	CHF C	CHF	0	CHF	0	CHF _	0		
* Impl. partner	CHF C	CHF	0	CHF	0			CHF	0
Subtotal	CHF 0.0	CHF	0.0	CHF	0.0				
* Time on project (hours)	0.00	ו	0.00 h		0.00 h				
* Surname			* First name						
* Year of birth			Nationality						
* Acad. level			since						
* Qualification			since						
* Research role in project									
	please select		* Ph.D. student	yes 🗌	no 🗌				
*Hourly rate in CHF	please select 0.00			yes 🗆	no 🗆				
			student * Position in	yes 🗆	no 🗆				
CHF		2nd	* Position in company *Place of	·	no □	CHF _	0		
*Employer	0.00		* Position in company *Place of work	·		CHF _	0	CHF	0
*Employer Wages covered by	0.00 1st project year	CHF	* Position in company *Place of work project year	3rd pro	oject year	CHF _	0	CHF	0
* Employer Wages covered by * Fed./CTI funding	0.00 1st project year CHF	CHF	*Position in company *Place of work project year	3rd pro	oject year	CHF _	0	CHF	0
*Employer Wages covered by *Fed./CTI funding *Impl. partner	0.00 1st project year CHF CHF	CHF CHF	*Position in company *Place of work project year 0 0	3rd pro	oject year 0 0	CHF _	0	CHF	0
* Employer Wages covered by * Fed./CTI funding * Impl. partner Subtotal * Time on project	0.00 1st project year CHF CHF CHF 0.00	CHF CHF	*Position in company *Place of work project year 0 0 0.0	3rd pro	oject year 0 0 0	CHF _	175968	CHF	179400

Please use the insert sheet on the last page in this document to insert here additional employees.

• To copy/paste tabs: "unlock" the document







Swiss Confederation

Federal Department of Economic Affairs, Education and Research EAER

Commission for Technology and Innovation CTI Innovation Promotion Agency

6.4. Information on total costs to be incurred by implementation partner(s)

	Equipment costs (6.1.)		Othe	r costs (6.2.)	Wage costs (6.3.)			ndividual ibutions
Company: 1plusX AG								
Cash contributions	CHF	0	CHF	20000	CHF	0	CHF	20000
Other contributions	CHF	0	CHF	0	CHF	179400	CHF	179400
Company:								
Cash contributions	CHF	0	CHF	0	CHF	0	CHF	0
Other contributions	CHF	0	CHF	0	CHF	0	CHF	0
Company:								
Cash contributions	CHF	0	CHF	0	CHF	0	CHF	0
Other contributions	CHF	0	CHF	0	CHF	0	CHF	0
Company:								
Cash contributions	CHF	0	CHF	0	CHF	0	CHF	0
Other contributions	CHF	0	CHF	0	CHF	0	CHF	0
Company:								
Cash contributions	CHF	0	CHF	0	CHF	0	CHF	0
Other contributions	CHF	0	CHF	0	CHF	0	CHF	0
Company:								
Cash contributions	CHF	0	CHF	0	CHF	0	CHF	0
Other contributions	HF	0	CHF	0	CHF	0	CHF	0
Company:								
Cash contributions	CHF	0	CHF	0	CHF	0	CHF	0
Other contributions	CHF	0	CHF	0	CHF	0	CHF	0
Contributions per heading	CHF	0	CHF	20000	CHF	179400	CHF	199400

Comments:

Please indicate any information that you feel will make the financial plan clearer. You may also use this field to explain any specific requests you may have.

6.5. Recapitulation of financial plan

6.5.1. Where do particular project costs arise?

Please note that this section is not for the purpose of indicating "who pays what" but rather "who uses the funds".

CTI / federal contribution + Cash contribution to research partner							
Institute	Equipment costs (6.1.) in CHF	Other costs (6.2.) in CHF	Wage costs (6.3.) in CHF	Total costs			
ETH DAL	0	0	175968	CHF	175968		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
Total by column	CHF 0	CHF 0	CHF 175968	CHF	175968		

Contribution made by implementation partner							
Company/institution	Equipment costs (6.1.) in CHF	Other costs (6.2.) in CHF	Wage costs (6.3.) in CHF		Total costs		
1plusX AG	0	20000	179400	CHF	199400		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
	0	0	0	CHF	0		
Total by column	CHF 0	CHF 20000	CHF 179400	CHF	199400		

6.5.2. Financial plan (overview)

			Tot	tal contributions imp				
Credit columns	Federal	Federal/CTI funding Cash contributions		n contributions	imple	ontributions by ementation artner(s)	Total costs	
Equipment costs (6.1)	CHF	0	CHF	0	CHF	0	CHF	0
Other costs (6.2)	CHF	0	CHF	20000	CHF	0	CHF	20000
Wage costs (6.3.)	CHF	175968	CHF	0	CHF	179400	CHF	355368
Total	CHF	175968	CHF	20000	CHF	179400	CHF	375368

The total cash contribution must be at least 10% of the federal contribution. If this requirement cannot be met, please explain why under 6.4 "Comments".

6.5.3 Annual instalments (for projects lasting more than one year)

Instalments	Federal/CTI funding			Total costs to be incurred by implementation partners	Subtotal		
1st year of project	CHF	87984	CHF		99700	CHF	187684
2nd year of project	CHF	87984	CHF		99700	CHF	187684
3rd year of project	CHF	0	CHF		0	CHF	0
Total	CHF	175968	CHF		199400	CHF	375368

7. Implementation (approval, secrecy, standard contract)

The applicants (i.e. project partners) hereby confirm that they took note of the provisions of the Federal Act of 14 December 2012 on the Promotion of Research and Innovation (SR 420.1); of the Federal Subsides Act of 5 October 1990 (SR 616.1); of the Research and Innovation Promotion Ordinance of 29 November 2013 (SR 420.11); of the CTI Funding Regulation of 13 November 2013 (SR 420.124.2).

Partial secrecy of the contents of the project must be expressly requested and justified by the applicants. If full secrecy is required, hence precluding consultation with experts, then the CTI may reserve the right to not review the application. The applicants also agree that if federal funding is granted, project execution procedures between the Federal Administration and applicants shall be subject to the provisions the enclosed standard contract. Any changes to the provisions contained therein must be agreed to in writing.

Comments:

Place and date
, Signature of main research partner
Alternative: automatic consent.
Instead of signing, please mail this application to
info@kti.admin.ch

Place and date
, Signature of authorized main implementation partner
Alternative: automatic consent.
Instead of signing, please mail this application to
info@kti.admin.ch

Documents attached:

Please note the CTI may not hand out the subsidy contract if both the signed IPR agreement and IPR declaration have not been sent to the CTI (except for projects without implementation partner). Although the funding application will be evaluated without these documents attached, we strongly recommend the project partners discuss all issues regarding the future IPR agreement as soon as possible.

http://www.kti.admin.ch/projektfoerderung/00032/00045/00049/index.html?lang=en

Please submit the application via e-mail only to info@kti.admin.ch

Beitragsgesuch_Final_210512_en_ONLINE.doc

Quick preliminary verification of your application

Please note that the information below covers only certain aspects of the entire formal review of your application. In order to increase your chances of success, we recommend that you use this information to check your application before sending it to us. The following points should be taken into consideration.

1.	Title	page
	11110	page

The research institution should be listed among those certified as eligible for CTI research funding;
Foreign research partners: The "Additional information for projects involving a foreign research institution" form can be downloaded
at www.kti.admin.ch, completed and sent to the CTI with your application. You can check in advance whether a project involving a
foreign research partner is eligible to receive funding by completing the "Bilateral R&D projects" form available at
http://www.kti.admin.ch/projektfoerderung/00213/00268/index.html?lang=en.
The company name must be inscribed in the Swiss trade register;
All contact details must be indicated in the application;
Only 1 discipline has been chosen;
The R&D project start date must be indicated (at least month and year);
The brief project description must not exceed 480 characters in length.

6. Financial plan

Inadequate financial plans are among most frequent reasons why an application is rejected for revision before it can be evaluated by CTI experts. If one of the following items is not correctly filled in, the office will return the application and ask you to provide the missing details. This is done before the application reaches the review stage where it is examined by experts in the corresponding research field.

6.0 Clarification of term "cash contribution"

A cash contribution is funding that the implementation partner uses to purchase equipment and materials for the research institute or to pay the wages of research staff. Examples of cash contributions include the following:

- Equipment costs: the implementation partner purchases equipment that will remain at the research institute after completion of the R&D project. The lending of equipment to the research institute for the duration of the R&D project (i.e. the equipment is returned to the implementation partner after completion of the project) is not considered a cash contribution.
- Other costs: the implementation partner buys materials for the research institute to be used for the R&D project and/or to build the prototype at the research institute. Typical cash contributions include payment of travel expenses or the purchase of consumable goods for the project.
- <u>Wage costs</u>: the implementation partner pays the salaries of researchers at the research institution. Here, the total calculation (max. hourly rate x number of hours) must not exceed the wage levels indicated by CTI.

6.1 Equipment costs

As a rule, CTI does not provide any funding to cover equipment costs. In rare case, CTI will pay for equipment for the research
institute (but never for the implementation partner). If you wish CTI to make an exception to this rule, please explain why either
directly under item 6.1.b or under 6.4 "Comments".

	Please indicate	where the	equipment wi	ll be	located both	n during t	the R&D	project and	after	completion
--	-----------------	-----------	--------------	-------	--------------	------------	---------	-------------	-------	------------

6.2 Other costs

As a rule, CTI does not provide any funding to cover other costs. In rare case, CTI will pay other costs for the research institute (but
never for the implementation partner). If you wish CTI to make an exception to this rule, please explain why either directly under item
6.2.b or under 6.4 "Comments".

CTI never provides funding to cover general expenses, travel expenses, general consumable goods and conventional software
icences.

6.3 Wage costs

- Make sure that wage costs do not exceed the wage levels established by CTI in the information sheet.
 Each R&D project may specify only 1 project manager (which must be the same person indicated on page 2) and 1 deputy project manager.
 The CTI does not cover salaries of tenured university professors. Their services should be part of the project plan but must not be listed in the financial plan.
 The project manager and deputy project manager may devote no more than 20% of their annual working time (i.e. 365 hours) to the
- the person's qualifications and experience up to the maximum hourly rate indicated for an "experienced researcher".

 For each person assigned to work on the R&D project, the following information must be provided at the very least: employer, level of education and training, role in project and hourly rate.

R&D project at the corresponding hourly rate. If this maximum threshold is exceeded, the hourly rate must be adjusted according to

The sub-totals must match. (CTI uses the following calculation: "hourly rate x number of hours"). If the total does not add up, the application will be returned for revision).

6.4 Information on total costs to be incurred by implementation partner

- The contributions listed in Table 6.4 must correspond to the totals indicated in Tables 6.1, 6.2 and 6.3.
- "Comments" field: please indicate any information that you feel will make the financial plan clearer. You may also use this field to explain any specific requirements you may have.

6.5 Recapitulation of financial plan

6.5.1 Where do particular project costs arise?

Please note that this section is not for the purpose of indicating "who pays what" but rather "who uses the money", regardless of who ultimately makes the contribution.

6.5.2 Financial plan (overview)

- The totals indicated in tables 6.1 "Equipment costs", 6.2 "Other costs" and 6.3 "Wage costs" should be indicated here.
- The total costs to be incurred by the implementation partner (i.e. cash and other contributions) must equal at least 50% of the total costs of the R&D project. If the amount is lower than 50% and you would nevertheless like CTI to consider the application, please indicate why under 6.4 "Comments". Of course, this option does not apply to R&D project proposals for which there is no implementation partner).
- The cash contribution must equal at least 10% of the federal contribution. If project partners are unable to meet this requirement, please provide a plausible explanation under 6.4 "Comments". In rare cases, CTI will make an exception to this rule.

IPR documents

If the application is being sent to the CTI without attached IPR documents, the official decision would, in case of project approval and funding, include at least the following preliminary conditions with a deadline of 6 months.

- CTI must receive a copy of the intellectual property rights agreement drafted in accordance with art. 41 of the Research and Innovation Promotion Ordinance (SR 420.11) and signed by all partners.
- CTI must receive a copy of the declaration on an agreement on intellectual property and usage rights according to the Research and Innovation Promotion Ordinance(SR 420.11) art. 41.

From experience CTI suggests to consider that the preparation of IP relevant documents may take longer than planned and therefore can cause a delay of the originally intended project start. We strongly recommend the project partners to discuss all IP relevant topics as early as possible.

http://www.kti.admin.ch/projektfoerderung/00032/00045/00049/index.html?lang=en

Insert sheets

Additional employees assigned to work on the R&D project

* Surname		* First name			ماه	CTI nare of costs	Implement share o	
* Year of birth		- Nationality		-	51	iare or costs	5115112	
* Acad. level		since		-				
* Qualification		- since		_				
	ease select	* Ph.D. student	yes no					
*Hourly rate in CHF		* Position in company						
* Employer		* Place of work		_				
Wages covered by	1st project year	2nd project year	3rd project year					
* Fed./CTI funding	CHF 0	CHF 0	CHF 0		CHF	0		
* Impl. partner	CHF 0	CHF 0	CHF 0			_	CHF	0
Subtotal	CHF 0	CHF 0	CHF 0					
* Time on project (hours)	h	h	h	1				
* Surname		* First name		_				
* Year of birth		Nationality		_				
* Acad. level		since		_				
* Qualification		since		_				
* Research role in project ple	ease select	* Ph.D. student	yes □ no □					
*Hourly rate in CHF		* Position in company						
* Employer		* Place of work		_				
Wages covered by	1st project year	2 nd project year	3rd project year					
* Fed./CTI funding	CHF 0	CHF 0	CHF 0		CHF	0		
* Impl. partner	CHF 0	CHF 0	CHF 0				CHF	0
Subtotal	CHF 0	CHF 0	CHF 0					
* Time on project (hours)	h	h	h	1				
* Surname		* First name		_				
* Year of birth		Nationality		_				
* Acad. level		since		_				
* Qualification		since		_				
in project	ease select	* Ph.D. student	yes □ no □					
*Hourly rate in CHF		* Position in company		_				
* Employer	T	* Place of work	Г	۱ ا				
Wages covered by	1st project year	2nd project year	3rd project year	4				
* Fed./CTI funding	CHF 0	CHF 0	CHF 0	$\ \ $	CHF _	0		
* Impl. partner	CHF 0	CHF 0	CHF 0	$\parallel \parallel$			CHF	0
Subtotal	CHF 0	CHF 0	CHF 0	$\ \ $				
* Time on project (hours)	h	h	h					
			total or carry-over		CHF	0	CHF	0

Additional Research-/ and Implementation partners

Research partner

*Surname		*First name	е			Title	/gender	
*Full name of institution	Short form	*Postal add	dress					
		Street:						
		Postal code:		Town:			Canton/ country	
Website / *E-mail:		*Tel.:			Fax:			

Implementation partner

*Surname	*First name	*First name			
*Full name of institution	*Postal addres	SS	'		
		Street:			
		Postal code:	Town:	Canton/ country	
Website / *E-mail:	*Tel.:	·	·		
Trade:	Number of em	ployees:			