

Conflict and Cooperation: AI Research and Development in terms of the Economy of Conventions

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Abstract

Artificial Intelligence (AI) and its relation with societies is increasingly becoming an interesting object of study from the perspective of sociology and other disciplines. Theories such as the Economy of Conventions (EC) are usually applied in the context of interpersonal relations but there is still a clear lack of studies around how this and other theories can shed light on interactions between human and autonomous systems. This work is focused into studying a preliminary step that is a key enabler for the subsequent interaction between machines and humans: how the processes of researching, designing and developing AI related systems reflect different moral registers, represented by conventions within the EC. Having a better understanding of those conventions guiding the advances in AI is considered as the first and required advance to understand the conventions afterwards reflected by those autonomous systems in the interactions with societies. For this purpose, we develop an iterative tool based on active learning to label a data set from the field of AI and Machine Learning (ML) research and present preliminary results of a supervised classifier trained on these conventions. To further demonstrate the feasibility of the approach, the results are contrasted with a classifier trained on software conventions.

Keywords

Automated content analysis, Economy of conventions, Neural networks, Text tagging, AI research, AI development

1 Introduction

In recent years the AI domain has experienced an impressive growth¹. Without any doubt, one could claim that it is a rapidly evolving field, with a strong research-oriented component. Whereas the majority of the research around the concept of AI is concentrated on how to build more precise, reliable and advanced models, the object of study of this paper is to analyse advancements in AI from a sociological point of view, with the perspective of deducing which 'conventions' or moral orders are employed during the creation of

these models based on dialogue and justifications between individual(s) and the collective. By this, we further shed some light on how the resulting product may affect the societies in which they are deployed.

The Economy of Conventions (EC) provides the framework for this study and is described in detail in *Section 2.1*. For the analysis of conventions, we create a real-world text data set and examine the distribution of conventions in this data set. We use an iterative training process based on active learning [47] to build a supervised machine learning model with one binary classifier per convention and show results on each convention. Furthermore, we compare this results with results from a classifier trained on software characteristics. Experiments, data and related code will be publicly released in the form of a Github repository. Link to the repository will be provided in future versions of this work.

1.1 Objectives

The purpose of this work is to study the presence of these conventions in the dialogues occurring during AI research, design and development phases. Research articles within the domain of ML and AI, and the dialogue within, as the researcher describe their findings to the collective, were assumed to reflect the conventions followed by scientists working in the field of AI research and design. Further, documents stored in open-source ML and AI software repositories, and the dialogues within, were assumed to reflect the conventions guiding decisions taken during the AI development phase.

1.2 Related Work

1.2.1 Economy of Conventions (EC) Although there is a large body of literature on understanding the motivations of open source software developers, a search for the use of EC in this context fails to produce satisfactory results. There is only one mention of EC in the context of software developing *Hurni et al. 2015* [29] where the authors apply EC in order to explain inter-organizational relationships in the coordination process of platform-based multi-sourcing.

Further non-technical approaches (*Denis et al., 2007* [18], *Gkeredakis, 2014* [22], *Kozica et al., 2014* [33]) use EC to explain coordination of pluralism and contradictory strategies in organizations.

¹Forbes, 10 charts that will change your perspective on AI growth: www.forbes.com/sites/louiscolombus/2018/01/12/10-charts-that-will-change-your-perspective-on-artificial-intelligences-growth/

In order to gain further insights, we replace the term “Economy of Conventions” with “motivation”, leading to additional results in the domain of software development. Especially in the field of open source software (OSS) development, motivation has been thoroughly researched. Previous research (*Bosu et al., 2019* [13], *Hertel et al., 2003* [27], *Roberts et al., 2006* [43]) identifies five primary categories of motifs:

- Intrinsic motivation i.e. fun or self-efficacy (*Ryan and Deci, 2000* [44])
- External rewards i.e. monetary incentives or career opportunities (*Lakhani and Wolf, 2003* [35])
- Ideology i.e. altruism (*Stewart and Gosain, 2006* [51])
- Community recognition i.e. fame or reputation (*Okoli and Oh, 2007* [39])
- Learning i.e. development of personal skills or knowledge (*von Krogh et al., 2012* [55])

While these categories can be partially linked to the EC, previous research fails to investigate this connection.

1.2.2 Content analysis of open source projects Github has been widely studied as source of information for software development projects in previous works. These efforts can be categorized as follows:

- **Users analysis** *Merelo 2016* [37] study the evolution of a specific community of users, *Montandon et al. 2019* [38] suggest a methodology to identify experts in the use of a given software library. *Hauff et al. 2015* [25] propose the idea of using Github user profiles to automatically match users to existing job offers.
- **Programming languages prevalence** *Bissyandé et al. 2013*, [6] and *Sanatinia et al. 2016* [46] study the popularity of different programming languages in a large number of Github projects.
- **Projects quality** *Cosentino et al. 2014* [15] study the openness of Github projects, *Borges et al. 2015* [12], study projects popularity and factors related to and affecting it. *Borges et al. 2018* [11] study common patterns in projects starring. *Horton et al. 2018* [28] study the executability of projects written in the Python language.
- **Project characteristics predictability** *Borges et al. 2016* [10] study the predictability of projects popularity, *Kapur et al. 2018* [30] consider the predictability of defectiveness in software code and *Sorbo et al. 2019* [50] propose a methodology for automatic identification of Github issues that would not been solved at any point in time.

Previous works focusing on the analysis of project content often apply a quantitative approach to reach an understanding of behaviour through the use of mathematical and statistical modelling or by reflecting a pattern in terms of numeric values *Chen et al. 2017* [14]. This approach is sometimes also combined with qualitative studies based on automated processes. An example of this, *Sharma et al. 2017* [48] can be seen in the combination of an automated topic extraction with manual validation, to perform an automated categorization of Github repositories based on the README files

content. *Hassan et al. 2017* [24] propose the use of both qualitative and quantitative approaches to automatically detect software building instructions in README files.

Apart from these efforts, *Prana et al. 2018* [41] show the benefit of automatically giving structure to the Github README file content. To do so, they combine manual annotation with automated text classification approaches to classify the content of the README files into a set of predefined categories: What, Why, How, When, Who, References, Contribution, and Others.

In the concrete field of analyzing content relating to machine learning and/or artificial intelligence in Github, *Zhang et al. 2019* [56] perform a qualitative analysis of the quality of software projects related to scientific articles in the field of AI.

This work proposes the categorization of AI and ML related projects based on the content of the projects README file and in the context of EC paradigm. The relationship between a projects popularity rating and their characteristics as per their framework categorization is also considered as first step to understand related factors. Although the content of Github README files has been previously studied, it has been with an alternative objective in mind.

1.2.3 Content analysis of scientific articles Although there is much work in quantitative analysis on scientific articles, this body of work is mainly focused around the extraction of various entity- and relation types (such as named entities, [3], coreferences [23] and semantic roles [26]. Accordingly, previous work analyzing Semantic Scholar focuses on those types [36]. Although there is work on identifying patterns within the research community, this work is concerned with structural analysis such as citations and gender [54, 54] and not with discourse patterns. Recent work on language modeling in scientific texts [5] reports state of the art results on several standard NLP tasks. However, such a model is generally not feasible for convention classification as this complex task requires in depth control of the iterative labeling- and classification process.

1.3 Structure of the paper

This paper is structured as follows: *Section 2: Economy of Conventions (EC)* provides an overview of the theory, *Section 3: Data set* covers the data collection process and an overview of the data collected *Section 4: Classification Model Architecture* describes the architectural pipeline of the model, *Section 5: Results* outlines the results of the experiments followed by *Section 6: Conclusion*.

2 Economys of Conventions (EC)

As discussed in *Section 1*, the main focus of the proposed work is on the intersection between the Economy of Conventions theory and the research, design and development of AI-related systems. The following sections gives an introduction to the EC theory.

2.1 Theoretical framework

The Economy of Conventions (EC), as a general social science theory developed by *Boltanski and Thévenot (2006)* [9], proposes consistent pragmatic concepts for the sociological analysis of behavioral coordination. It relies on the justifications observed during ordinary disputes. This framework of justification is conceived as

a theoretical research lens to study empirical conflicts. In conflict situations, actors mobilize arguments to defend their perspective. Based on field surveys and Western political philosophy, Boltanski and Thévenot developed a taxonomy of the various conventions, or registers, of the “common good” mobilized by the actors. The common good – or the benefit or interests of all – directly refers to specific perceptions of justice and fairness (*Boltanski and Thévenot 2006* [9], *Diaz-Bone 2018* [19]). Hence, when a conception of the common good based on one principle of justification is criticized according to criteria based on another, (potential) conflicts arise. This theoretical approach has been already used in many different fields, e.g. production of consumer goods (*Storper and Salais 1997* [52], *Boisard 2003* [7]) and health (*Da Silva 2018* [16], *Sharon 2018* [49], *Batifoulier et al. 2018* [4]). It was found to be useful for gaining more insight into what is at stake in emerging conflicts. *Boltanski and Thévenot (2006)* [9] identified six justification registers, each based on different philosophical foundations in Western liberal societies and conceptions of justice and what is fair: civic, industrial, commercial, domestic, inspired, and renowned. It was expanded with two more registers, the ‘project’ and the ‘ecological’ (*Boltanski and Chiapello 2005* [8], *Lafaye and Thévenot 1993* [34]). *Sharon (2018)* [49] introduced a further register based on the ‘googlization of health research’. Table 1 provides an overview of each of these registers with their principles of justification:

Register	Common good	Values
Industrial	Increased efficiency	Functionality, expertise, optimization
Project	Innovation and the network	Activity, experimentation, connection
Market	Economic growth	Competition, consumer choice, profit
Inspired	Inspiration	Spontaneity, deliberation, emotion
Civic	Collective will	Inclusivity, solidarity, equality
Domestic	Tradition	Hierarchy, trust
Green	Protection of environment	Environmental activism
Renown	Public opinion	Popularity, fame

Table 1: Registers of worth

Following table 1, there is a plurality of possible conventions or registers. The term ‘convention’ or ‘register’ in the EC does not simply mean a habit or custom (*Boltanski and Thévenot 2006* [9], *Thévenot 2001* [53]). Rather, the concept of convention in the EC is more complex. Conventions and registers can be understood as interpretative frameworks developed and managed by actors to evaluate and coordinate action situations (*Diaz-Bone, 2019* [20]). This does not imply that each individual is part of a particular register, nor that individuals consciously act according to the precepts of any of these mentioned (*Da Silva, 2018* [16]). On the contrary, actors, depending on interactions with others, can easily pass ‘from

one register to another’ (*Da Silva, 2018* [16]). Similarly, the justifications given to each of these activities are implicit; individuals will only explain them in a conflict. Coordination requires agreement on a common principle or on the realization of an understanding, which can emerge between different registers of justification. There is no register more rational than any other to the extent that they all refer to a legitimate and immeasurable conception of the collective. The decision is not just a matter of calculation but a choice between several possible commons (*Diaz-Bone, 2018* [19]). Each register acts as a logical, harmonious order of statements, objects and people that provide a general sense of justice. Hence, the typology of *Boltanski and Thévenot (2006)* [9] offers an applicable framework for identifying the registers, which guide developers and their moral orientations in smart cities.

3 Data set

This section describes the collection of the data set used for the building of the classification models described in Section 4. The data set comprises of documents from two main sources: GitHub README files and paper abstracts from Semantic Scholar (S2). Web documents are also included to add variety to the data set and domain-specific documents provide information on the EC. The next section describes the iterative approach used for the collection of data to train the classifier models used to perform the experiments for collected information.

This section describes the approach taken for the collection of the required data to facilitate the analysis of conventions followed by practitioners when researching, designing and developing AI systems.

3.1 GitHub

From a high level perspective, GitHub is a web-based interface and cloud-based service that provided developers with the tools to effectively store and manage their code, in addition to tracking and controlling changes in the code base.

Containing the code and metadata of more than 100 million projects with involvement from more than 31 million developers², GitHub is a valuable source of information for the understanding of open source software development properties and dynamics, it is for this reason that GitHub was thought to be a useful source of data required to facilitate the execution of the objective, that is, the uncovering of the conventions that software developers follow while engaging in the implementation of open source AI and ML development projects. In particular, the manner in which conventions are reflected through the project creators choice of language to “sell” the capabilities and benefits of their creations.

GitHub can be considered as a web-based extension of Git³, a tool created with the goal of managing software development projects and their files, as they evolve over time. Git stores this information in a data structure known as a repository.

A repository is a central location where developers store, share, test and collaborate on their projects. Typically, a git repository contains a README file, oftentimes containing an elaborate description of the project and its objectives. GitHub README files in

²“Thank you for 100 million repositories”, <https://github.blog/2018-11-08-100m-repos/>

³GIT webpage:<https://git-scm.com/>

particular are deemed to be a key source of meaningful data as these files are present in a high proportion of GitHub projects and contain information related to the project purpose, usefulness, execution, description, support and maintenance procedures. Collaboration guidelines and software licenses can also regularly be found.

GitHub data was accessed through the official GitHub API. Filtering by featured Machine-Learning topic, information of more than 8.500 projects are collected. Between the obtained information, the content of the README file, repository creation and last update timestamps and statistics about its popularity are collected. To avoid possible biases, examples from all different levels of popularity, according to the GitHub star rating, are collected.

To compare the prevalence of the obtained results in the ML arena, data from an large number of randomly selected projects from topics unrelated to ML are also collected. Based on the observation that projects with lower popularity ratings have shorter descriptions and therefore, less informative results of conventions classification identified from their README, the selection of repositories for this second data set was done with the purpose of having examples from all straits of popularity, according to the number of stars.

The statistics of the data sets collected from GitHub are summarized in *Table 2*:

GitHub Data	Repositories	Sentences	Avg. stars
AI topic	8609	138085	271.43
Other topics	5358	76 274	453.52

Table 2: GitHub data statistics

Analyzing the programming languages used in each data set, Python is the most common programming language for the AI topic data set with 38.97% of support and *Javascript* is the most used in the data set containing repositories not related to AI, with a 25.56% of support.

3.2 Semantic Scholar (S2)

Semantic Scholar (S2) is a search engine for peer-reviewed articles, which provides an open research corpus with more than 40 million papers from computer science and bio-medicine in machine readable JSON format [1]. For the analysis of the conventions, we select a sample of entries that appear in one of the AI conferences listed in [31], which are published after the year 2017. With the help of this list, the use of conventions in different sub-fields of AI, such as robotics, computer vision and natural language processing can be analyzed. To further narrow down the use of conventions we are using a list of keywords which belong to either register presented in Table 1 to help pre-filter documents for the classification (KW), which is established by the authors of this paper. We only select publications from the year 2017 onward because during this time, research in AI and applications of ML in particular received a significant boost with the release of Tensorflow [2]. In this manner we collect a sample of 4.051 paper abstracts. The data set is provided.

The following tables describe the S2 data. *Table 3* shows the size of the original data, the general number of submitted abstracts during the time span of the analysis as well as the subset of matches

of the KW out of a sample of AI conference, which we analyze. *Table 4* shows the distribution of conventions in our final data.

S2 Data	Abstracts	Sentences
S2 complete	40mio	120mio
S2 > 2016	4mio	20mio
S2 sample AI + kw > 2016	4.051	32.454

Table 3: S2 Data statistics

Convention	Abstracts	Sentences
Project	725	5776
Inspired	66	506
Renown	130	1076
Market	324	2630
Domestic	326	2710
Green	139	1173
Industrial	2048	16264
Civic	293	2319

Table 4: Distribution of Conventions in S2 sample AI + KW

4 Classification Model Architecture

Text classification is the process of assigning tags or categories to text according to its content. Texts are usually classified on either the level of word, sentence, paragraph or document. The objective being to automatically classify a group of given text units into a set of predefined categories or classes, to enhance decision making in a fast and cost efficient way. To automate the analysis and classification of data from the selected sources, text classifiers based on ML and deep learning approaches are employed with consideration given to the coverage of certain necessary user cases for the task at hand.

The collection of correctly labeled training data is also critical to any successful ML implementation. Deep learning, and more generally ML practitioners rely on this data for the creation of sufficiently accurate prediction models. Due to the domain expertise necessary to correctly determine which convention from the EC is reflected in a specific sentence, in addition to the shortage of labelled training data at the offset of the research an active learning design methodology was employed as part of the architectural pipeline.[47]

4.1 The problem of multi-class classification

In ML, classifying instances into one of two classes or categories is known as binary classification, multi-class classification is the problem of classifying instances which can be of three or more classes or categories. As there are eight conventions in the EC framework the solution permits the use of more than two classes. Some classification algorithms naturally permit this concept while others must be architect specifically to support this functionality. Various strategies exist to extend the use of a binary classifier to cater for multi-class classification. For the purpose of this paper, a strategy commonly known as one vs. rest (or one vs. all) was employed Rifkin et al. 2014 [42]. This involved training a binary

classifier per class (one binary classifier per convention). This also requires that the base classifiers produce a real-valued confidence score for the classification decision, rather than just a class label.

4.2 The problem of Multi-Label Classification

Multi-label classification originated from the need to categorise text where each instance may belong to several predefined labels simultaneously. One record can have multiple labels and the number of labels per record is not fixed. Due to the nature of the EC, whereby a given sentence can reflect any number of given convention to varying degrees, the solution supports multi-label classification. Multi-class classification differs from multi-label classification in that in a multi-class problems the classes are mutually exclusive, whereas for multi-label problems each label represents an independent classification task.

4.3 Model selection

As proposed by Kim 2014 [32], convolutional neural network is trained with the vectorization of texts based on word GloVe Pennington et al. 2014 pre-trained word embeddings. With an architecture, which involves training a binary classifier per class (in this case this translates to one binary classifier per convention). As previously mentioned, this strategy requires the base classifiers to produce a real-valued confidence score for the decision, rather than just a class label. To this end and following the one versus all methodology, one individual classifier C_c is trained per convention C . Given a sentence S the classifier C_c is trained such that it assigns a probability score P for that sentence being part of the convention C . Therefore: $C_c(S, C) = P$ where $P = [0, 1]$.

As result of this process, a collection of $N = 8$ (one per convention) binary classifiers are used to predict the probability of an observation(sentence) belonging to each possible class label(convention). The models are trained with calibrated precision. The approach was selected due to the inherent existence of features considered to be key to a successful outcome, including:

- The support of multi-class classification, where more than two categories for classification exist.
- The support of multi-label classification, where one record can have multiple labels and the number of labels per record is not fixed.
- The identification of the absence of any convention in a given sentence. To facilitate this requirement an alternative architecture would necessitate the gathering of examples not reflective of a convention, this was considered to be a complicated task.
- The possibility, if necessary, to use a different pre-trained word embeddings for one or more of the classifiers

4.4 Word Embeddings

Generally speaking, in ML implementations the process of training a classifier requires that data inputs be in the form of numeric values rather than continuous or discrete variables. The first step towards training the classifiers therefor is to use a feature engineering method to numerically represent the training text in the form of a vector. Traditional (count-based) feature engineering strategies rely on models belonging to a family commonly known as the “Bag

of Words” model. This includes such strategies as term frequencies, term frequency-inverse document frequency (TF-IDF), N-grams etc. The most common state of the art approach however is that of word embeddings. Word embedding refers to the transformation of words into n-dimensional vectors projected into a new multidimensional space. Until the appearance of word embeddings, the main drawback of alternate solutions is the lack of precision when dealing with these contextual relationships. Using word embeddings, words and therefore sentences having a similar context will have this contextual relationship reflected within the n-dimensional space whereby words with similar context and meaning will appear closer together in this space.

4.5 Data Tokenisation

Sentence granularity is selected as the approach for the implementation of the convention classifier. It is considered that paragraphs might easily represent more than one convention whereas a sentence would have a higher likelihood of reflecting a single convention.

4.6 Training data and Active learning

As previously mentioned, the collection of correctly labeled training data is critical to any successful ML implementation, to this end an active learning model is implemented with a focus on uncertainty sampling.

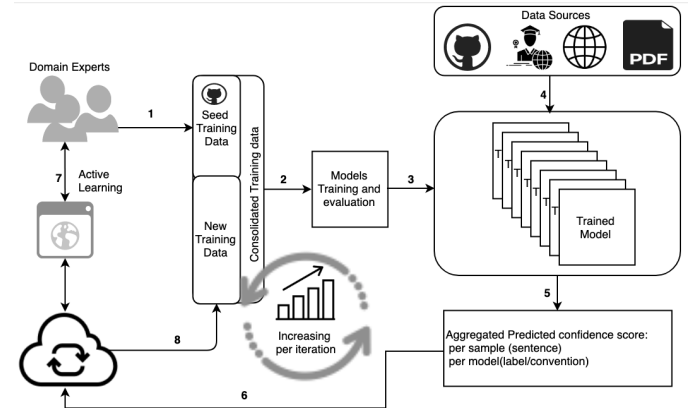


Figure 1: Active learning based data flow to assist with collection and verification of additional training data

- (1) A randomly sampled subset of sentences gathered from GitHub is manually labelled by domain experts. This 'seed' data is leveraged as a starting point for the production of accurate classification models .
- (2) This initial labelled data is used for the first iteration of training for each of the eight models.
- (3) The models are trained, performance is evaluated and the first set of models ready for use are produced, one per convention.
- (4) The trained models are used to classify sentences gathered from a variety of sources including GitHub, Semantic scholar,

web documents and domain specific documents related to the various EC conventions.

- (5) The outputs of these classifications, a probabilistic confidence score, per sentence, per model, are aggregated. The confidence score indicates the probability that a sentence belongs to a particular convention. After aggregation there are eight probabilistic scores per sentence.
- (6) The aggregated data containing each sentence and its associated probabilistic scores is pushed to a centralised cloud service and consumed by a web based active learning tool (a python notebook, with IpyWidgets driven interactive GUI, deployed on a Jupyter based virtual machine using Binder (<https://mybinder.org/>). Since the labeled data should be representative of the range of unlabeled data available, an automatically generated histogram is made visible via the active learning tool, to provide insight for the domain expert in relation to the most beneficial areas of focus.
- (7) The Domain experts use the active learning tool to either validate that the classification is correct, or to correct the classification. Common practice in active learning is to focus on validating or correcting decisions on either side of the models 'decision boundary', in other words on the boundary, separating a particular model's confidence in a positive versus negative prediction (that a sentence is part of a convention or that it is not). To this end, a filter is provided on the tool to allow the domain experts narrow the focus of the active learning session to the areas around the decision boundary.
- (8) If the domain expert determines that the label applied by the model for an unseen sentence is correct, the label is accepted and the sentence is automatically added to the training data for the next iteration of learning. Otherwise the domain expert is given the option to correct label and/or to correctly classify the sentence as part of one of the other conventions whereupon this re classified sample is also automatically added to the training data for the next iteration. Finally, as part of the active learning process, a separate algorithm is applied to the combination of new and old training data to ensure that there are equal numbers of positive and negative examples per convention (and hence per model), this is to avoid any problem with data imbalance. These steps 3 to 8 are a regularly repeated sequence of events, resulting in the growth of labelled training data

4.7 Keywords

We use two sets of keywords to pre-filter documents: First, we use a keywords list, which is manually created by domain experts and one of the authors and which is based on the registers introduced in 2.1. Second, after collecting the training data set using the flow explained in the section above, Term frequency-inverse document frequency(TF-IDF) algorithm [45] has been used to extract those terms (key words) that are more common for each convention and not so common in the rest. Table 4.7 contains the top three most relevant terms for each convention according to the TD-IDF score.

As can be observed, it confirms that collected data is properly representing the conventions as the top terms are totally meaningful.

Convention	Top key words
Industrial	efficiency, functionality, benchmarks
Project	projective, employability, engage
Market	buy, customers, buyers
Inspired	emotion, theorem, sophisticated
Civic	solidarity, representative, union
Domestic	manners, law, generation
Green	growth, carbon, sustainable
Renown	press, media, famous

Table 5: Top keywords by TF-IDF + manually created by convention in training data

5 Results

Between the obtained results, a quality assessment of the classifiers is performed and afterwards, an study on the results of evaluating Github and Semantic Scholar data using the classifiers is explained.

5.1 Classifiers

This section contains a set of experiments done with the purpose of evaluation the quality of the created models. To do so, the performance of the classifiers is evaluated with the following metrics:

- **Area under curve (AUC):** AUC score provides an aggregate measure of performance across all possible classification (confidence) thresholds. AUC can be interpreted as the probability with which a model ranks a random positive example higher than a random negative example.
- **Precision:** Precision is the ratio $tp/(tp + fp)$ where tp is the number of true positives and fp the number of false positives. Precision is intuitively the ability of the classifier not to label as positive a sample that is negative.

The quality of each of the created models on unseen data is independently evaluated by using both metrics using cross validation based on leave-one-out splitting.

Convention	Accuracy	AUC	N	$E_{prevalence}$
Industrial	0.914	0.886	1342	1/10
Project	0.787	0.751	630	1/100
Market	0.885	0.872	578	1/100
Civic	0.849	0.825	466	1/100
Inspired	0.806	0.772	346	1/1000
Domestic	0.840	0.777	364	1/1000
Green	0.875	0.873	1574	1/10000
Renown	0.833	0.794	308	1/10000

Table 6: Comparison of evaluation metrics

Table 6 contains the average score for each classifier according to the selected metrics: a value N with the number of training

samples gathered for each convention and a value $E_{prevalence}$ referring to the estimated prevalence of each convention in GitHub, estimated by observation. Conventions with a high discrepancy between N and $E_{prevalence}$ are those with no training samples in Github or Semantic Scholar, so we gather training samples from the other sources mentioned above. The table is sorted by the value of $E_{prevalence}$ column. Learning curves provide insight on the amount of labeled data, the classification models require to achieve good results and the amount needed to improve. To do so, a cross-validation generator splits the whole dataset $k = 10$ times in training and test data. Subsets of the training set with varying sizes are be used to train the estimator and a score for each training subset size and the test set is computed. Afterwards, the scores are averaged over all k runs for each training subset size.

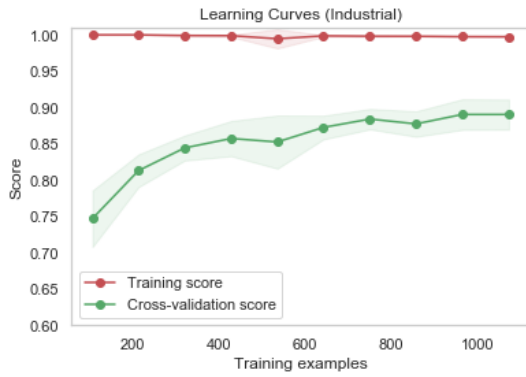


Figure 2: Learning curves for Industrial convention classifier

Figure 2 depicts the learning curve for the Industrial convention, the one with most samples in the data set. For this classifier, the performance stabilizes after 800 samples. Learning curves for the rest of the conventions will be added in future versions of this document.

The classifiers output is a value in the range $[0, 1]$. To separate positive matches (convention found) from negative ones (convention not found), a threshold $T_{calibration}$ has been calculated for each of them and equalize precision at value 0.9. This procedure is known as calibration [17] and is applied to equalize the precision classification ratio between all the models so further analysis are not biased by different precision scores.

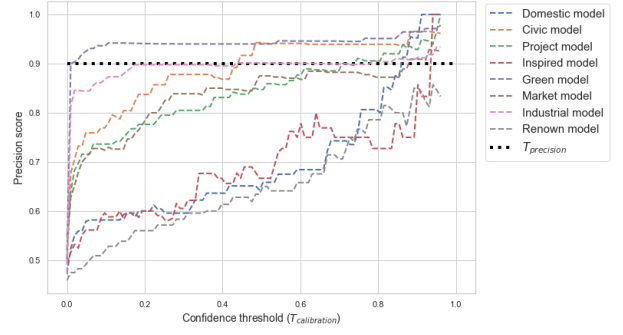


Figure 3: Precision curve for each EC classifier with the precision threshold at value 0.9

The $T_{calibration}$ threshold (point of intersection between the precision curve for each of them and the horizontal line) lies at $y = 0.9$. The precision curves and their cut with the precision value of 0.9 are depicted in Figure 3.

A confusion matrix is used in multi-class classification tasks to understand how well each classifiers differentiates between samples from different classes. In this case, as it is possible that a sentence matches positively by more than one classifiers, rows of the confusion matrix are normalized by the total number of examples having a certain true label. For this analysis, the classifier for the Renown convention has not been considered as it does not reach the precision value of 0.9

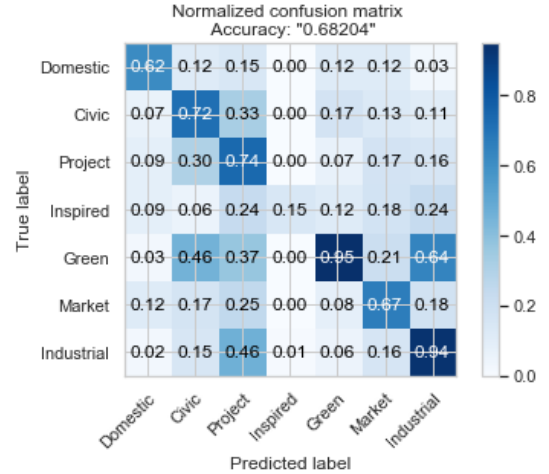


Figure 4: Confusion matrix of EC classifiers using the obtained calibration threshold

The confusion matrix using the precision calibration threshold $T_{calibration}$ for each classifier is depicted in Figure 4. As can be observed, although all classifiers except the one for the Inspired convention are correctly (above 65%) matching samples for their convention, there is a lot of confusion between certain classifiers. This errors will be addressed in future versions of this document

by carefully adding to the training data those samples from other classes that classifiers are not able to differentiate.

5.1.1 Performance with different word embeddings To execute this experiment, two different word embeddings are considered: GloVe Pennington et al. 2014 [40], trained on Wikipedia and Gigaword corpora in one hand SO embeddings Efstathiou et al. [21] trained with a corpus extracted from Stack Overflow.

The vocabulary size for each word embeddings is summarized in Table 7.

Embedding	Vocabulary size	Context
Glove	400000	General purpose texts
Stack Overflow	1787145	Computer science

Table 7: Statistics of used word embeddings

As proved in [21], the word embeddings trained on Stack Overflow perform better at capturing technical-related terms representations for those words with polysemic meanings. As the objective of this work is to analyze Github and Semantic Scholar, a-priori containing technical content, the performance of the classifiers using one and the other embeddings is compared.

To assess this experiment, the performance for the Industrial and Green conventions is compared for each word embeddings, as they are respectively understood as more-technical and less-technical domains from the perspective of the computer science discipline.

Results are calculated using the average of $N = 10$ independent executions with a Leave one out cross validation approach. The performance is evaluated using prediction accuracy over the set of data not used for training.

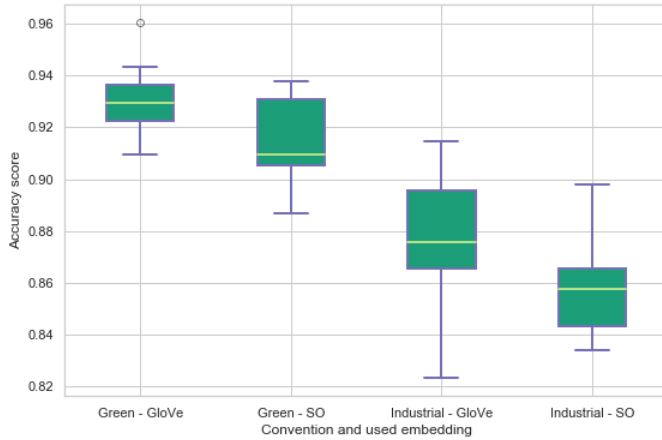


Figure 5: Classifiers performance with different embeddings

As can be observed in Figure 5, models using GloVe embeddings outperform those models that are trained Stack Overflow word embeddings. This effect happens for both the Green and Industrial

conventions. This is a very interesting result, as we consider it counter-intuitive as the embeddings performing worse are trained for the specific context of computer science and have bigger vocabulary size.

Although the implemented classifiers architecture opens the door for using different word embeddings, even for each convention, the results shown prove that understanding if a certain word embedding will help to increase the performance of the system is an arduous task.

5.2 Conventions in datasources

In the following experiments, analysis of conventions identified by using the built classifiers is discussed.

5.2.1 Conventions in AI and non AI sources The purpose of this experiment is to compare the presence of conventions in AI related Github repositories with the conventions identified in Github repositories from other topics that are not AI related. To do so, the created classifiers are used to extract matches for each repository and results are then aggregated for all the repositories within AI and not AI topics and papers from AI and not AI domain. For this experiment, the Renown classifier was not considered as its precision was not reaching the specified value of 0.9 for any confidence threshold.

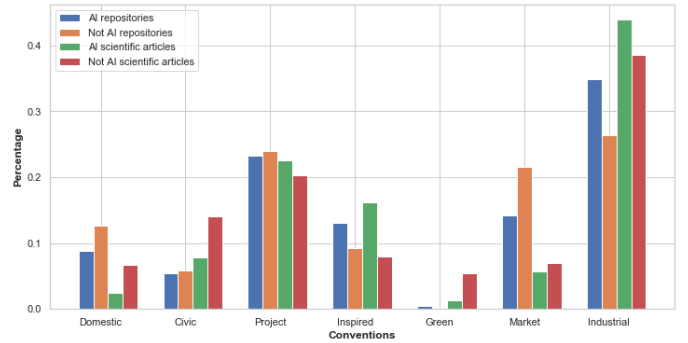


Figure 6: Comparison of conventions in GitHub repositories classified as AI and not AI

The result of the experiments can be observed in Figure 6 and, as can be observed, different meaning full interpretations can be extracted from it. In general, the results are highly correlated between all data sources. The observed prevalences are also pretty aligned with the estimated ones, and the Industrial convention is dominating in all the sources, the Project is the second more common where as the Green convention is scarcely found. Seems like a Market convention is widely more present in Github repositories than in scientific articles and there is an important difference in the presence of this convention between AI and not AI repositories.

5.2.2 Relation to software characteristics There have been some efforts on standardizing methodologies that help on the assessment of software quality. In this contexts, industry standards such as ISO 9126⁴ describe a categorization of characteristics to be

⁴ISO 9126: <https://www.iso.org/standard/22749.html>

considered on a software quality test. In this experiment, the relation between EC and the categorization provided by such standard is addressed. In concrete, the collection of classes was as follows:

- **Functionality.** "A set of attributes that bear on the existence of a set of functions and their specified properties. The functions are those that satisfy stated or implied needs."
- **Usability.** "A set of attributes that bear on the effort needed for use, and on the individual assessment of such use, by a stated or implied set of users."
- **Efficiency.** "A set of attributes that bear on the relationship between the level of performance of the software and the amount of resources used, under stated conditions."
- **Maintainability - Reliability.** Although separated in the ISO definition, both classes are merged as differentiating between them was not an easy task affecting the quality of the training data collection task. Maintainability is defined as "A set of attributes that bear on the effort needed to make specified modifications." Reliability is defined as "A set of attributes that bear on the capability of software to maintain its level of performance under stated conditions for a stated period of time." Portability. "A set of attributes that bear on the ability of software to be transferred from one environment to another."

To this well-established list, we propose the addition of the following aspects:

- **Advantages.** "Set of characteristics when compared with state of the art/market competitors". It is important to remark that advantages can be only be described by comparison, otherwise it might corresponds to functionalities.
- **Contributions.** "Whether the description specifically talks and allows other users to contribute by extending or work on the software". We added this feature as explicitly mentioning contributions for the project might be directly connected with the civic world (collective building of software).

At last, the type of license constraining the re-use and distribution of the software can be understood as potential cost and for that reason will also be considered:

- **License (Ownership/Costs).** "Availability and constraints governing the use or redistribution of the software."

The objective of this experiment is then to analyze correlations between the matches of each convention classifier with others trained for software characteristics using an equivalent training data gathering approach. To perform the correlation analysis, results for both types of classification are independently aggregated in a repository basis. Therefore, for each repository, the proportions of matches was obtained to avoid the results to be affected by repository README files content length.

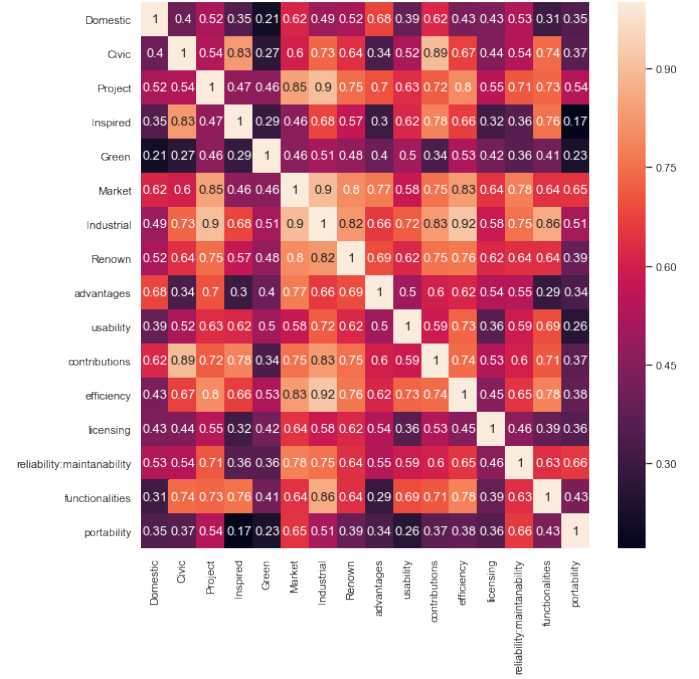


Figure 7: Correlation between classifications of economics of conventions and software characteristics classifiers

Figure 7 depicts the obtained results for the correlations analysis between conventions and software characteristics on Github data. Equivalent analysis will be performed for Semantic Scholar in next versions of this work. Although giving an deeper interpretation to the obtained results can exceed the purpose of this paper, there are at least two correlations that captured our attention: between the obtained values, the high correlation of the *Industrial* conventions matches with the software characteristics of *efficiency* and *functionalities* is aligned with the expectations. The same happens with the *Civic* convention and the *contributions* characteristic.

6 Conclusion

In this work, we described approaches both to analyze and predict conventions according to the EC. We created a data set mainly from two sources of scientific research: paper abstracts from scientific conferences and software development and analyzed the distribution of conventions in each sub-domain. We developed an interactive architecture based on active learning both to support domain experts in labeling data and select the most valuable data points to train machine learning classifiers. Preliminary results on the ML classifiers trained on the EC showed promising results. In an additional study, the results were contrasted with the results from a classifier trained on software conventions and we have shown comparable and understandable results on both theoretic frameworks. An evaluation of different word embeddings showed that, counter to our expectations, our model performs better when we use general-purpose embeddings than with domain-specific ones. In further steps, one focus will aim to detect and analyze common

conflicts in software development and their underlying (assumable conflicting) conventions, beyond the already obvious problems of coordination between open source- and profit oriented AI development. By this, we hope to contribute to a more plural understanding of AI research and development, considering underlying moral registers which influence the motivations, objectives, processes and values of these projects.

6.1 Limitations

The explained approach uses sentence-level tokenization for the classifications. According to EC literature, conventions are better reflected on discussions where individuals need to defend their positions. Future work can focus in using current shape of the EC classifiers to analyze other data sources that, if having a conversational nature, will be better confronting and reflecting the conventions.

Further, we have observed that the proposed techniques are highly dependent on the collection of high quality training data. Although an approach to facilitate such gathering has been proposed, further advances might be required to reduce the amount of manual work to be done by a human data labellers.

We have recently identified a required improvement for the models evaluation results. As most of the quality metrics are calculated considering models independently but they are used together afterwards. In this regard methodologies of "Micro-averaging Macro-averaging" can be applied to obtain the individual models performance and overall metrics respectively. This will be addressed in future versions of this document.

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