

Combining Truth Discovery and Open Information Extraction with Active Ensembling

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ABSTRACT

Web search engines or open information extraction systems usually reply to users' queries with a set of candidate answers that are often conflicting because they are claimed by multiple information sources. In this context, estimating information veracity is difficult for the users especially when they have no prior knowledge about the trustworthiness of the sources. In this demonstration paper, we showcase a system that supports event/entity and relation extraction based on keyword-search from the Web, processes the conflicting outputs, combines multiple truth finding algorithms with active learning to provide the most likely true answers and determine the most trustworthy sources.

1. INTRODUCTION

[Lamine: Page allocation]

- 1.25 pages -> abstract + introduction
- 1.5 pages -> Open information extraction + Active Ensembling for Truth Discovery
- 1 pages -> Demonstration System + Scenario
- 0.25 pages -> References

2. OPEN INFORMATION EXTRACTION

- décrire le type d'information auquel on s'intéresse par exemple "factoid claim"
- décrire le système sur lequel on se base
- décrire comment on transforme l'output de OpenIE
- donner qq exemples

In this study, we are interested on truth discovering over the huge number of "factoid" statements (or claims) about real-world facts returned by information extraction systems. These claims are extracted from unreliable Web sources. A "factoid" claim, e.g., *Barack Obama was born in Kenya*, is a piece of unverified or inaccurate information that is presented as factual, often as part of a publicity effort. Such type of claims is usually accepted as true because of its frequent redundancy over multiple sources. We focus on

conflicting factoid claims provided by typical open Web information extraction systems as answers to users' queries. Concretely, given user input, we retrieve the set of candidates claims, together with the associated sources, returned by TextRunner¹ from a Web corpus. We then format this output in such a way that fits our truth discovering process.

Data collection. We analyze claims about real-world facts from TextRunner. TextRunner is an open Web information extraction system relying on an unsupervised extraction process on a fixed collection of Web corpus consisting of Google, ClueWeb, News, Nell, and Wikipedia corpus. Each particular corpus aggregates information from multiple other Web sources which can be of different nature, e.g. domain specific sources. When a query is issued, TextRunner first searches for the relevant corpus to query, and it then extracts the possible answers from them. To do so, it performs, for efficiency concerns, a single data-driven pass on the corpus to obtain the list of candidate relational tuples which might satisfy the user input query about a given real-world fact. In TextRunner, a user input query is typically a set of keywords consisting of two real-world *entities* and a *relation*. Such a user input query q can be defined formally as a triplet (e_1, r, e_2) where e_1 and e_2 are real-world entities and r is a relation. The argument r specifies a possible relationship that might exist between the two given entities. None of the three arguments is mandatory, meaning that some of them can be not specified by the user when issuing his query. This captures the fact the user has a partial knowledge about the real world, which is common in practice. Let denote the fact the user input query q is referred to by f_q . TextRunner will find and extract a collection of Web claims related to this fact.

TextRunner's output is thus a set of candidate claims about a specific real-world fact. This output is ranked by the system according to the number of sources that supports each claim. A claim in this context can correspond to a tuple, a relation, or an real-world entity with respect to the given keywords. TextRunner also offers the ability, through Web hyperlinks, to access to the meta-data, e.g., the source, the type, the full corpus, etc., associated to each returned claim for further exploration.

Data formatting. Given a user query q about a fact f_q , we consider the set C_q of n claims c_1, \dots, c_n extracted by TextRunner as answers to the query q . For each claim c_i ,

1. TextRunner is accessible online at <http://openie.allenai.org/>

Figure 1: Data collection and formatting

$1 \leq i \leq n$, we go through the attached Web hyperlink and extract the set \mathcal{S}_{c_i} of sources which support it. We achieve such a extraction by using hand-written mapping rules. We have also assumed that the system returns only one claim per source for a given query, i.e., $\mathcal{S}_{c_i} \cap \mathcal{S}_{c_j} = \emptyset$ for all $i \neq j$ with $1 \leq i \leq j \leq n$. We have now, for the query q about the fact f_q , the set of claims together with the sources. In order to fit to the input of the truth finding process, we need to format the data collected from TextRunner about the facts in a certain manner. As a consequence, for the fact f_q , we therefore consider every extracted claim c_i and generate a triplet (f_q, c_i, s_j) for each source $s_j \in \mathcal{S}_{c_i}$. We finally obtain a collection of triplets $\{(f_q, c, s) \mid c_q \in \mathcal{C}, s \in \mathcal{S}_c\}$ as the final formatting of the output of TextRunner regarding a given user input query q about a fact f_q .

[Lamine: **Quelle types de requêtes souhaitons nous supporter?**]

[Lamine: **Si on considère chaque requête séparée, on se retrouve à traiter un seul claim à chaque fois. Généraliser à k requêtes utilisateurs?**]

[Lamine: **Peut être qu'il serait interessant d'avoir une idée de la distribution du nombre de conflits per query sur TextRunner**]

3. ACTIVE ENSEMBLING FOR TRUTH FINDING

We describe in this section our use of active ensembling in the context of truth finding for discovering gradually the optimal set of algorithms that together maximizes the accuracy of the process when users' feedbacks arrive into the system.

3.1 Ensembling

- donner idée générale pour introduire ce qu'est l'ensembling
- on a besoin de le faire dans le contexte de truth discovery car aucune methode ne bat toutes les autres dans tous les cas de figure
- donc on combine les methodes : il y plusieurs façon de combiner par ex. consensus de méthodes, etc.
- expliquer quelles méthodes on combine avec leurs avantages et inconvénients

Ensembling, or commonly ensemble-based active learning, is a semi-supervised learning method that learns about an appropriate combinaison of multiple classifier types for a given task by interactively querying users (or other types of sources) for *labeled examples*.

In our setting, we are interesting on discovering the optimal combinaison among several possible truth finding algorithms which correspond to our classifier types. This combinaison is excepted to maximize the precision of the truth finding process on claims outputted by TextRunner as possible answers with respect to a user's query about a given real-world fact. A well known lack, e.g., as shown in [5, 8], of existing truth discovering algorithms is that they are mostly sensitive to particular application domains and data characteristics. As a consequence, there is no approach that out-

performs the others on all types of datasets. Furthermore, the truth finding process is harder in practical scenarios in the sense that there usually exists no labeled examples, or *ground truth data*, against which one can evaluate the precision of the different algorithms in order to choose the more accurate one on data of interest. Fortunately, however, human being has often a certain knowledge background about certain real world facts. The user knowledge is a valuable source of labeled examples that should be harnessed as partial standard for evaluating the accuracy of our truth finding process. Indeed, even though a partial ground truth data could be obtained from the users, an optimal truth finding strategy change over time as we obtain more data from sources, for instance when claims are continuously extracted from Web sources by TextRunner. To tackle the aforementioned lacks of existing truth finding algorithms, especially in real applications like information extracted systems, we will use an active ensembling in truth finding in order to continuously discover an optimal hybrid truth finding approach when the extractor is gradually queried and users' feedbacks arrive. As we shall show later, we will actively involve users for labeled example in our ensemble-based learning process.

Determining the optimal sample of unlabeled items to send to the sources, e.g., users, for labels during an active learning problem is a challenging problem. Several query strategies, e.g., uncertainty sampling or query by committee, or Support vector machine (SVM) models have been proposed for the definition of such a optimal sample of data. Note that the type of the selected data along with the size of the sample are crucial for the effectiveness of the learning procedure; we defer to [7] for more details about active machine learning. In this study, we have used query by committee strategy which consists of training a variety of classifiers on the current labeled data, and vote on the output for unlabeled data; label those points for which the "committee" disagree. Query by committee is known to be efficient for finding an optimal set of ensemble methods using active learning.

[Lamine: **J'ai juste mentionné "query by committee" in guise d'exemple. La stratégie utilisée doit être choisie.**]

We use and compare twelve well established truth finding algorithms in the literature, which we cluster in different classes according to their specificities. We briefly present each class of considered truth discovering algorithms in the following.

1. **Iterative techniques:** TruthFinder [12], Cosine, 2-Estimates and 3-Estimates [3], AccuNoDep [1]
2. **EM based techniques:** MLE [10], LTM [13], SimpleLCA and GuessLCA [6]
3. **Dependency detection based techniques:** Depen, Accu, and AccuSim [1]

[Lamine: **La classification des algorithmes est juste une proposition. Peut être qu'il existe une meilleure classification.**]

3.2 Active Learning Process

- notre approche que l’on défend ici dans la démo est semi supervisée en impliquant de l’utilisateur de façon active en lui demandant s’il peut confirmer des faits (facts)
- si on a une ground truth partielle on la ”rejoue” cas par cas

We rely on an ensemble-based semi-supervised learning process for discovering an hybrid, i.e., an optimal ensemble of truth finding algorithms for information extraction systems. Let denote by \mathcal{Q} the set of successive user queries processed by the information extraction system. For each query q in \mathcal{Q} about the fact f_q we have the corresponding sets of claims \mathcal{C}_q returned by the extractor. We refer to the entire set of all claims by \mathcal{C} regarding \mathcal{Q} . We assume that \mathcal{C} contains labeled and unlabeled claims where labeled claims, corresponding to our partial ground truth, are those for which we know whether they are correct or not by querying the user. In contrast, we do not know yet the truth about unlabeled claims and would like to discover by using the best ensemble of truth finding algorithms. We refer respectively to labeled and unlabeled set of claims by \mathcal{C}^L and \mathcal{C}^U . Given a base learning algorithm X , a number k of fixed act iterations, and a fixed size m of a sampling, we perform ensembling on our set of truth finding algorithms as follows.

1. We first select a committee of classifiers (here, truth finding techniques) using our base learning algorithm and the labeled claims \mathcal{C}^L .
2. We then discover the true values for unlabeled claims in \mathcal{C}^U using the chosen committee
3. We select a subset T of m true claims
4. We request labels for these claims to the user (our oracle here).
5. We lastly remove claims in T from \mathcal{C} and them to \mathcal{C}^L .

4. OUR DEMONSTRATION SYSTEM

We describe in this section our system for combining truth discovering and information extraction with active ensembling. We first present the architecture of our system by giving its different modules. Then, we provide a typical demonstration scenario of a user interacting with our system.

4.1 GUI and System architecture

The architecture of our demonstration system, given in Figure 2, comprises the following three main components.

Graphical user interface. It represents the main entry point of our application for user interaction. The user I/O interface is composed by a text search area where a given user can enter its search keywords, in terms of a relation. The final result of the overall process will be also show to the users through this component. Finally, the user gives it feedbacks via the user I/O interface through the button options or the form.

Information extraction module. This is the information extraction module which considers the input of the user and browsers several Web sources in order to returns the relevant answers. In our system, we rely on TextRunner in order to extract information from Web corpus.

Truth Finding Module. It corresponds to AllegatorTrack which contains twelve truth finding algorithms with different accuracy according to the types of claims and the characteristics of sources.

Active Ensembling Module. We have also a learning method that uses our knowledge bases of users feedbacks. It enables to learn about the best truth finding algorithms, among the twelve, to use with respect to the type of entities or relations searched by the user.

Repository of Labeled Facts. The knowledge base contains the information used for the learning phase the truth finding procedure. These information include the true facts for some relations which have been learnt based on the feedbacks of the users. In addition, our knowledge base could be enriched with ground truth about some facts from reliable sources such as Wikipedia. Based on the knowledge base, our system has the ability to improve the accuracy of the truth finding process by learning about the best method to use or the best parameters, e.g., sources’ accuracy scores, to consider for a better bootstrapping of the process.

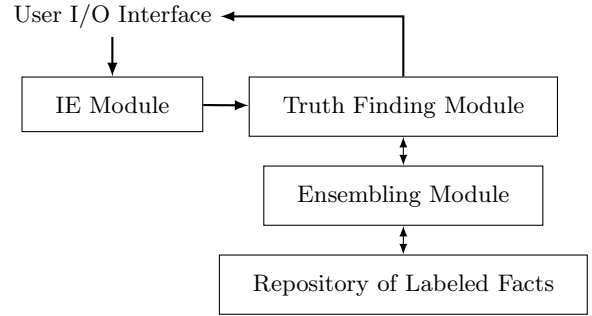


Figure 2: Architecture of our system

4.2 Demonstration scenario

A given user that wants to interact with our system must do it through the search form. Through the search form, she (or he) provides her searched relation, e.g., “Where is born Barack Obama?”. The searched relation is then passed to the information extraction engine, TextRunner system in our case, which returns a set of answers considered to be relevant for the user’s request. Each claim in the returned list is processed in order to extract the corresponding sources along a detailed description of the claim which we format in a certain manner. The set of sources and the formatted versions of all claims are then passed to the truth finding module which integrate all the claims and compute the most probable answer together with the reliability scores of participated sources for the searched relation. Finally, the output of the truth finding process is returned to the user. The user can also want to review the output of our system by definitively validiting it or not through its knowledge of the modeled world. For example when the system has totally wrong, it may be interesting to get such a kind of feedbacks from the user in order to change the used method, as there are many available with our system, and to enhance the process for the further search about the same world. The user gives feedbacks using the option buttons on the left-hand

side of the outputted claims or the text form. The feedbacks given by the user is saved in knowledge bases within our system for further processes.

5. CONCLUSION

[Lamine: **L'utilisateur peut faire une erreur sur l'étiquette de certains claims. Comment capturer ce phénomène?**] []

6. REFERENCES

- [1] Xin Luna Dong, Laure Berti-Equille, and Divesh Srivastava. Integrating conflicting data: The role of source dependence. *PVLDB*, 2(1):550–561, 2009.
- [2] Oren Etzioni, Michele Banko, Stephen Soderland, and Daniel S. Weld. Open Information Extraction from the Web. *Commun. ACM*, 51(12):68–74, December 2008.
- [3] Alban Galland, Serge Abiteboul, Amélie Marian, and Pierre Senellart. Corroborating Information from Disagreeing Views. In *WSDM*, pages 131–140, 2010.
- [4] Naeemul Hassan, Chengkai Li, and Mark Tremayne. Detecting check-worthy factual claims in presidential debates. In *Proc. CIKM*, pages 1835–1838. ACM, 2015.
- [5] Xian Li, Xin Luna Dong, Kenneth Lyons, Weiyi Meng, and Divesh Srivastava. Truth finding on the deep web: Is the problem solved? *Proc. VLDB Endow.*, 6:97–108, December 2012.
- [6] Jeff Pasternack and Dan Roth. Latent Credibility Analysis. In *WWW*, pages 1009–1020, 2013.
- [7] Burr Settles. *Active Learning*. Number 114. Morgan & Claypool Publishers,, June 2012.
- [8] Dalia Attia Waguih and Laure Berti-Equille. Truth discovery algorithms: An experimental evaluation. *CoRR*, abs/1409.6428, 2014.
- [9] Dalia Attia Waguih, Naman Goel, Hossam M. Hammady, and Laure Berti-Equille. AllegatorTrack: combining and reporting results of truth discovery from multi-source data. In *Proc. ICDE*, pages 1440–1443, 2015.
- [10] Dong Wang, Lance M. Kaplan, Hieu Khac Le, and Tarek F. Abdelzaher. On Truth Discovery in Social Sensing: a Maximum Likelihood Estimation Approach. In *IPSN*, pages 233–244, 2012.
- [11] Alexander Yates, Michael Cafarella, Michele Banko, Oren Etzioni, Matthew Broadhead, and Stephen Soderland. TextRunner: Open Information Extraction on the Web. In *Proc. NAACL*, pages 25–26. Association for Computational Linguistics, 2007.
- [12] Xiaoxin Yin, Jiawei Han, and Philip S. Yu. Truth Discovery with Multiple Conflicting Information Providers on the Web. *TKDE*, 20(6):796–808, 2008.
- [13] Bo Zhao, Benjamin I. P. Rubinstein, Jim Gemmell, and Jiawei Han. A Bayesian Approach to Discovering Truth from Conflicting Sources for Data Integration. *PVLDB*, 5(6):550–561, 2012.