Dipartimento di Ingegneria e Scienza dellInformazione

– KnowDive Group –

Media Indexing

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1 Input Datasets Description

Event recognition is a challenging Computer Vision task in which the event represented in an image or in a video is retrieved by using a classifier. To do that, a training is needed but the labels are often provided with different annotations which make difficult a possible merging operation. Thus, the goal of this work is to provide a merged view of three well-known event recognition datasets (see Table 1) provided by Professor Francesco De Natale [1][2], which will help in the extraction of information from each dataset and the merging operation of the datasets, avoiding the issue of data and labels heterogeneity.
The dataset have been integrated under the aspects of:

- *Event*: it has been added a *PriorClass* which groups and makes homogeneous the different dataset labels.
- *Event*: the presence of people in the images carries an important information and merges the datasets.
- *Provenience*: the provenience of the dataset.
- *Organization*: the owner of the dataset helps in integrating the datasets.
- *Place*: the place of the event helps in integrating the dataset contents each other.

The USED dataset [1] is composed by 525000 social network images which are arranged in 14 different types of social events where each class has 35000 images. In [1] the label of each image is provided into a single *.txt* file named as the event class and containing the names of all the images belonging to this class. The EiMM dataset [2] is composed of 32973 social network images divided into two classes of events (social and sport) where each one is subdivided into other subclasses with a total number of 18 classes between social and sport events. In [2] the labels are provided in a *.xml* file associated to each image where are included file information(ex. creation date, dimensions and name) and the class information. Finally the SED dataset [3] is composed by 167332 social network images divided into 3 classes. In [3] the labels are provided into a single *.xml* file in which are present all the labels with many other information that are: the location, the GPS coordinates, the name of the event, the author of the file and the URL of the file in the web servers. In Table 1 all the initial information about the datasets images are reported in order to provide a general view of the starting point of this work while in Table 2 the classes of each dataset are reported to give a complete view of the heterogeneity.

Dataset	**USED** [1]	**EiMM** [2]	**SED**[3]
Classes	14	18	3
Location	no	no	yes
GPS	no	no	yes
Time	no	yes	yes
Event description	no	no	yes
Photo URL	no	no	yes
Format	JPEG	JPEG	JPEG
Online	yes	yes	yes
Organization	MMLAB	MMLAB	MediaEval

Table 1: Brief summary of the information available for each dataset.

It is important to notice that none of the used datasets has a complete *.csv* file including the information reported in Table 1, they were all sparse between images, *.xml* files and websites of the dataset. Managing all the entire datasets should be too expensive, thus representative sub-sets of each dataset has been used as starting data for our work[1]. The first step of this work has been the generation of the *.csv* files[2] to provide an initial view of the available information. In addition, to exploit the available information from the images, the presence of people in a part of the images in each dataset has been verified and detected using a cascade of three Person Detectors [3]. Thanks to the work of [4], provided by Professor Fausto Giunchiglia [4], an initial entity oriented model has been localized and then adapted in the domain of this work, see Section 1.

Dataset	Classes
USED [1]	concert, conference,exhibition, fashion, protest, sports, theater, graduation, mountain trip, meeting, pic-nic, sea holiday, ski holiday, wedding
EiMM [2]	concert, graduation, mountain trip, meeting, pic-nic, sea holiday, ski holiday, wedding, baseball, basketball, bike, cycling, F1, golf, hockey, rowing, figure skating, swimming
SED [3]	soccer, technical, indignados

Table 2: Classes of each considered dataset.

After the data indexing, data cleaning and data preparation operations, the full initial data have been reported in four different *.csv* files [4] and the classified and ordered sub-datasets in folders[5].

2 ER Model design and Ontology description

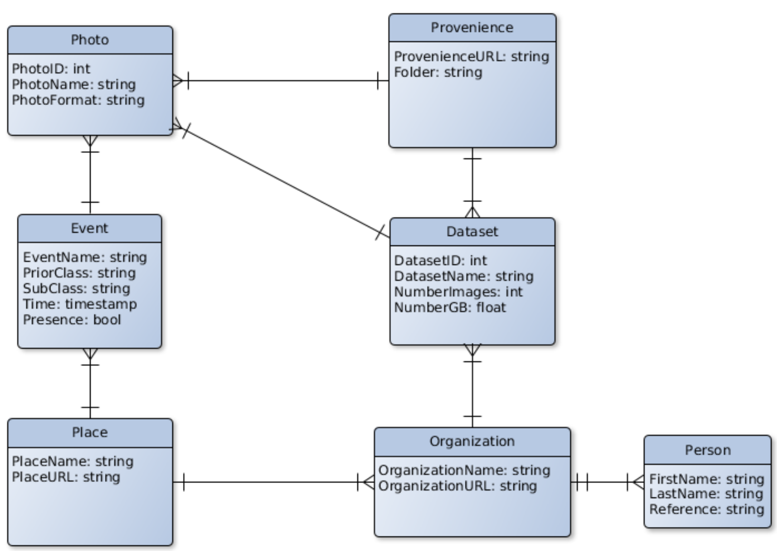

Figure 1: ER model.

[1] https://github.com/UniTN-KDILab/Data-indexing-2018-19/blob/master/SCRIPTS/classified_dataset_URL
[2] https://github.com/UniTN-KDILab/Data-indexing-2018-19/blob/master/SCRIPTS/generate_csv.py
[3] https://github.com/UniTN-KDILab/Data-indexing-2018-19/blob/master/SCRIPTS/classify.m
[4] https://github.com/UniTN-KDILab/Data-indexing-2018-19/blob/master/CSV
[5] https://github.com/UniTN-KDILab/Data-indexing-2018-19

In this work we expand the entity oriented model proposed in [4] adding other important attributes and entities present in our domain. So, the final ER-Model[6] used and proposed in this work is shown in Figure 1. This model has been obtained by using the software *yEd* which provides all the possible functions for the generation of ER models.

The entities reported in the proposed ER-Model are related to the entity classes described by the People Event Images (PEI) Ontology, Figure 2 which is proposed in this work.

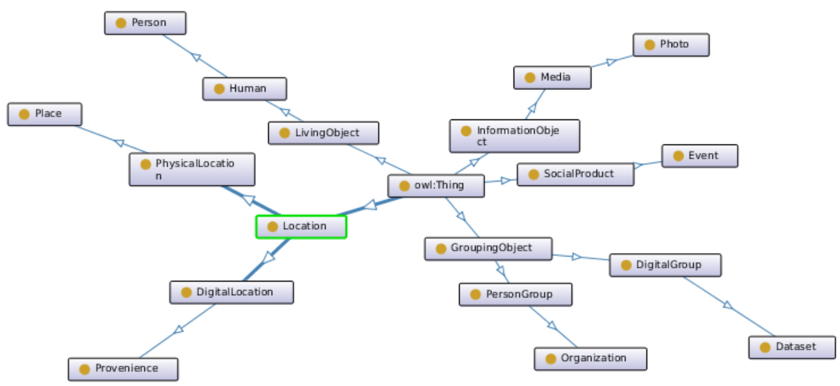

Figure 2: Graph of the PEI ontology.

From the Figure 1 it is possible to see that the connected entities are the entities: Photo, Provenience, Event, Organization, Person, Dataset and Place. These entities are all related and formalized in the following presented ontology. The PEI ontology is a small ontology which relates seven low level entity classes with different attributes and relations. Implemented using *Protègè* [7], this ontology includes the following classes:

Photo is a *Sub-Class of* the class *Media* which is a *Sub-Class of* the upper level class *InformationObject* due to the fact that in our domain the interest is in the semantic content of the image, thus, the information carried:

- *PhotoID* [integer] is an unique identifier of the file in the dataset;
- *PhotoName* [string] is the name of the file (without the extension);
- *PhotoFormat* [string] is the file extension.

Provenience is a *Sub-Class of* of the class *DigitalLocation* which is a *Sub-Class of* the main class *Location*:

- *Provenience URL* [string] is the URL of the dataset website at which is available the dataset;
- *Folder* [string] is the local directory path of the data.

Event is the class of the content if the scene in an *InformationObject* which is a *Photo*. It is a *Sub-Class of* the upper class *SocialProduct*:

[6] https://github.com/UniTN-KDILab/Data-indexing-2018-19/blob/master/ER/KDI-ER.png
[7] https://github.com/UniTN-KDILab/Data-indexing-2018-19/tree/master/OWL

- *EventName* [string] is the name of the event;
- *PriorClass* [string] is the type of event and it can be Social or Sport;
- *SubClass* [string] is the subclass of the type of event, i.e. Concert;
- *Time* [timestamp] is the date and time of the data acquisition;
- *Presence* [boolean] is the attribute which refers to the presence or absence of people in the data.

Dataset is a *Sub-Class of* the class *DigitalGroup* which is a *Sub-Class of* the upper class *GroupingObject*, it is a group of *InformationObject* which are *Media* of the *Sub-Class Photo*:

- *DatasetID* [string] is the unique identifier of the dataset (i.e. 1,2 or 3);
- *DatasetName* [string] is the name of the dataset;
- *NumberImages* [integer] is the total number of images in the dataset;
- *NumberGB* [float] is the size of the dataset data (in [GB]).

Place is the *Sub-Class of* the class *PhysicalLocation* which is the *Sub-Class of*. It is a *Sub-Class of* the upper level class *Location* as the class *DigitalLocation* due to the fact that they are both locations, one in the digital space and one in the space:

- *PlaceName* [string] is the name of the place;
- *PlaceURL* [string] is the URL to the *GoogleMaps* page of the *Place*.

Organization is the *Sub-Class of* the class *PersonGroup* which is *Sub-Class of* the upper class *GroupingObject*. It is under the same upper class of *DigitalGroup* being a group of entities of a class, in this case, of the class *Person*:

- *OrganizationName* [string] is the name of the Organization;
- *OrganizationURL* [string] is the URL to the web page of the Organization.

Person is a *Sub-Class of* the class *Human* which is the *Sub-Class of* the upper class *LivingObject*:

- *FirstName* [string] is the first name of the person;
- *LastName* [string] is the last name of the person;
- *Reference* [string] is the contact to the person, usually the email adress.

The above classes are related following the *Properties* which are all *Sub-Class of* the upper level property *Relations*:

isPhoto is a *Sub-Class of* the property *Composition* and the inverse of the property *hasPhoto*. It relates the class *Photo* to the classes:

- *Dataset*: it is a *Photo* part of the *Dataset* class;
- *Provenience*: it is a *Photo* at the given *Provenience*;
- *Event*: it is the *Photo* of the *Event*.

isEvent is a *Sub-Class of* the property *Composition* and the inverse of the property *hasEvent*. It relates the class *Event* to the classes:

- *Photo*: it is the *Event* in the *Photo* object;
- *Place*: it is the *Event* in the given *Place* object.

isPlace is a *Sub-Class of* the property *Placement* and the inverse of the property *hasPlace*. It relates the class *Place* to the class:

- *Event*: it is the *Place* of the *Event* object.

isOrganization is a *Sub-Class of* the property *Composition* and the inverse of the property *hasOrganization*. It relates the class *Organization* to the classes:

- *Dataset*: it is the *Organization* owner of the *Dataset* object;
- *Place*: it is the *Organization* which is located in the given *Place*;
- *Person*: it is the *Organization* of the member *Person*.

isPerson is a *Sub-Class of* the property *Composition* and the inverse of the property *hasPerson*. It relates the class *Person* to the classes:

- *Organization*: it is the a member *Person* of the *Organization*.

isDataset is a *Sub-Class of* the property *Composition* and the inverse of the property *hasDataset*. It relates the class *Dataset* to the classes:

- *Organization*: it is the *Dataset* object property of the *Organization* object;
- *Provenience*: it is the *Dataset* of the given *Provenience* object;
- *Photo*: it is the *Dataset* container/group of the *Photo* object.

isProvenience is a *Sub-Class of* the property *Placement* and the inverse of the property *hasProvenience*. It relates the class *Provenience* to the classes:

- *Dataset*: it is the digital *Provenience* of the *Dataset* object;
- *Photo*: it is the digital *Provenience* of the *Photo* object.

It is important to note that the above *Relations* all follows the links and the cardinality expressed by the ER-model 1 and formalized in the OWL file of the PEI ontology.

3 Integration process description

The initial dataset were provided without *.csv* files and without any possible file with merged information. Being required a *.csv* to proceed with the mapping of the dataset, it has been used a python3 script[8] to generate the normalized *.csv* files for each dataset and for the upper properties of the datasets[9]. The obtained normalized files have been named as:

- EiMM_dataset.csv;
- SED_dataset.csv;

[8] `https://github.com/UniTN-KDILab/Data-indexing-2018-19/tree/master/SCRIPTS/`
[9] `https://github.com/UniTN-KDILab/Data-indexing-2018-19/tree/master/CSV`

- USED_dataset.csv;
- datasets.csv.

In all the _dataset.csv files the columns are organized to report all the same attributes for each class, in order:

- *Photo*:PhotoID, PhotoName, PhotoFormat;
- *Place*: PlaceName, PlaceURL;
- *Event*: Time, PriorClass, SubClass, EventName, Presence;
- *Provenience*: ProvenienceURL ,Folder;
- *Dataset*: DatasetName.

While in the datasets.csv file, the columns contains the following class attributes:

- *Person*:FirstName, LastName, Reference;
- *Organization*: OrganizationName, OrganizationURL;
- *Provenience*: ProvenienceURL ,Folder;
- *Dataset*: DatasetID, DatasetName, NumberImages, NumberGB.

It is important to notice that in many cases, the *.csv* fields were not all filled by the script due to the absence of these attributes in the dataset or due to the excessive complexity in filling it with python. Thus the obvious solution has been to fill the empty fields with python, when the information was easy to be handled with a script, and to hand-fill the empty fields with a *.csv* editor when the information was not included in the dataset(i.e. ProvenienceURL, EventName, and often Time) or if it was too complex to handle them with a python script. At this point, observing the previous attributes, it is clear that the *.csv* files have been normalized also under the name aspect. Thus, by using the *Karma* Data Integration toolkit, it has been conducted the formal mapping of the normalized *.csv* files over the PEI ontology obtaining a mapping model R2RML[10], a RDF file[11] and a Raw JSON file[12] for each *.csv* file. An example of a mapping over a _dataset.csv file is reported in Figure 3 while the mapping over the datasets.csv file is reported in Figure 4. Being the *.csv* file of each dataset normalized, the same mapping has been used over eac dataset.

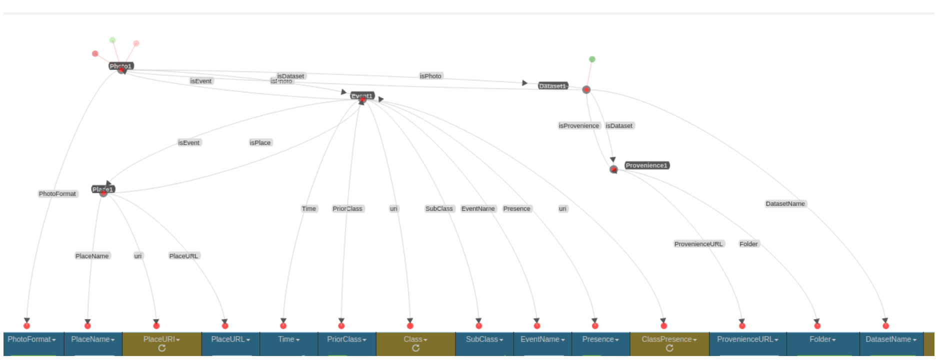

Figure 3: Mapping of the EiMM_dataset.csv over the PEI ontology.

[10] https://github.com/UniTN-KDILab/Data-indexing-2018-19/tree/master/R2RML
[11] https://github.com/UniTN-KDILab/Data-indexing-2018-19/tree/master/RDF
[12] https://github.com/UniTN-KDILab/Data-indexing-2018-19/tree/master/JSON

In the mapping, they have been defined URIs for some useful class using the PyTransform function in *Karma*. To enter into details, in each *.csv* of a dataset, five URIs have been instantiated for the classes:

- *Photo*: the URI has been called *PhotoURI*, it reports the fields "http://PEI_project/"+*DatasetName*;
- *Place*: the URI has been called *PlaceURI*, it reports the fields "http://PEI_project/Places/"+*PlaceName*;
- *Event*: the URI has been called *Class*, it reports the fields "http://PEI_project/"+*PriorClass*+"/"+ *SubClass*;
- *Event*: the URI has been called *ClassPresence*, it reports the fields "http://PEI_project/Presence"+ *PrioprClass*+"/"+*Presence*;
- *Dataset*: the URI has been called *DatasetURI*, it reports the fields "http://PEI_project/Datasets"+ *DatasetName*;

While in the datasets.csv file, two URIs have been instantiated for the classes:

- *Organization*: the URI has been called *OrganizationURI*, it reports the fields "http://PEI_project/"+ *OrganizationName*+"/"+*FirstName*+"_"+*LastName*+":"+*Reference*;
- *Dataset*: the URI has been called *DatasetURI*, it reports the fields "http://PEI_project/Datasets"+ *DatasetName*;

These lasts URIs are also visible in Figure 4.

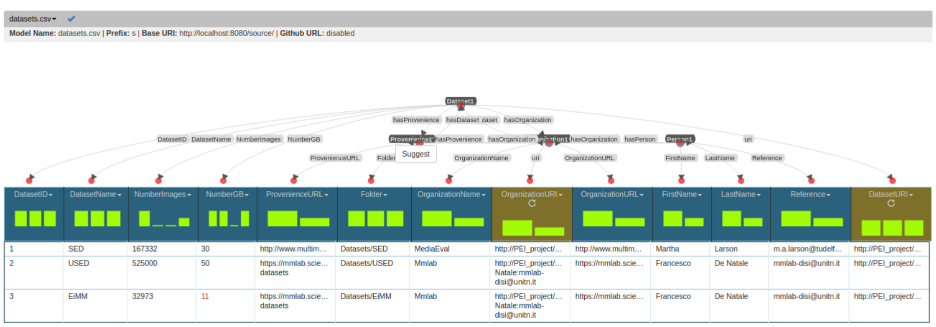

Figure 4: Mapping of the datasets.csv over the PEI ontology.

Thanks to the mapping with *Karma*, the *.csv* files have been formally mapped on the PEI ontology thus retrieving to each class the belonging attributes. Finally, thanks to the URIs, the RDF files now correctly maps the attributes and the information of each dataset into the PEI ontology under the http directory "http://PEI_ontology/".

4 Output Dataset and queries description

In this Section a description of the output obtained by the mapping and a proposal of possible queries, solved thanks to the data integration of this work,is proposed. Thanks to the formal mapping of the data on the PEI ontology using *Karma* and thanks to the normalization process done by using the python script, at this point it is possible to analyze the different datasets with the same normalized attributes while relating them with a formal ontological class of the PEI ontology. So, if an attribute, i.e. PhotoName, of the SED [3] dataset is analyzed,

thanks to the formal mapping on the PEI ontology, it is possible to correlate it with a given class i.e. Photo. The addition of many attributes(i.e. Presence) conducted automatically or by hand, permits to observe the content of each dataset enabling to a very high number of possible queries extracted from the output of this work. Due to the large number of possible queries, here are reported only representative examples which exploits the main points of our work. In addition, it is important to notice that in the indexing conducted in Section 1-3, implicit queries have been proposed and solved while proceeding in the integration of the datasets. These queries, now completely answered thanks to the integration, were the first two presented in the following examples. The first main query, root of this work, was:
Which is the PriorClass of the events in the dataset EiMM?Is there a common class of all the SubClass?
Now, thanks to the output of our integration, this query is easy solvable by using Rapidminer, in fact, in Figure 5 it is clear the answer.

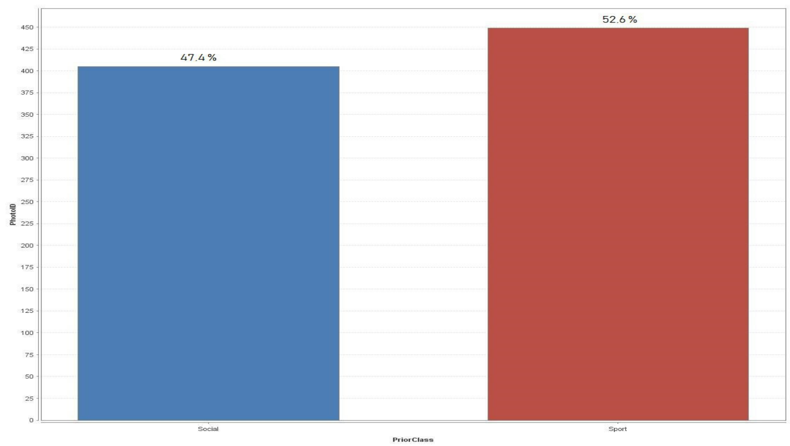

Figure 5: Social Events vs Sport Events in the EiMM[2].

The second main query of this work is the following:
In how many Social and Sport events are present people?
Thanks to the integration and to the indexing of this work, now it is possible to have the answer to this query in Figure 6.

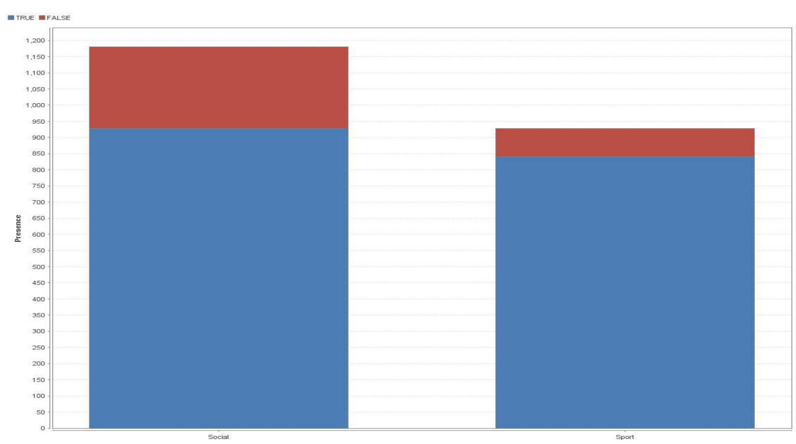

Figure 6: Presence(blue) of people in Social and Sport events in the EiMM [2] dataset.

And the previous query is also expandable to the entire database w.r.t. each SubClass thanks to the normalization and mapping of the datasets on the PEI ontology, see Figure 7.

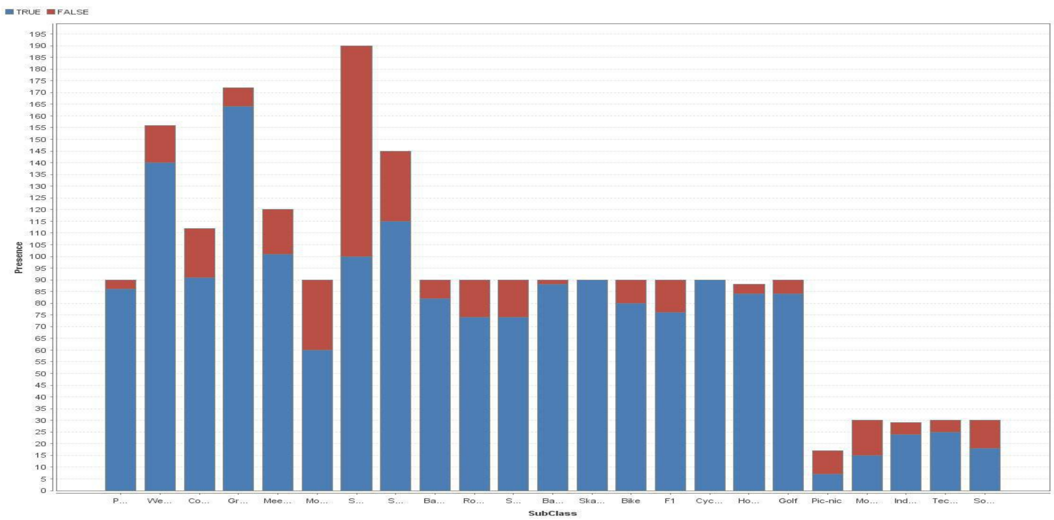

Figure 7: Presence of people in the images of the output database.

These exposed are only few of the aimed queries thanks to our work, other possible queries could be:

- Where are mainly located the Social/Sport events in the dataset?
- In the organized events in Hamburg, is there a high Presence?
- What are the trend SubClass of events in the given Place?
- For this research we need Social events, is this dataset useful for us? Which is its composition?

And the answers to the previous queries are now fully facilitated by the output of this work.

5 Input/Output Dataset comparative analysis description

This section analyzes the input and output datasets on the basis of their completeness, heterogeneity and queries. First a short description of the input datasets [1] [2] [3] is given (see Section 5.1 for a detailed description). Then, the output datasets are analyzed (see Section 5.2) in order to underline the key differences after the data integration process performed in this work, which are briefly summarized in Table 3.
It is important to notice that here attributes and classes are reported with the PEI annotations while in the annotations of each dataset they were often named with different names. This normalized description is conducted in order provide a description in the same analysis domain.

5.1 Input Datasets

The final output database is composed by the three input datasets described in Section 1. As said before, these datasets were selected in order to perform the integration of the data in a smart way such that at the end, the final product will be useful for many tasks (see 6).

Going more into details, the input datasets considered were extremely heterogeneous under the annotation and composition points of view. As reported in Table 3 and introduced in Section 1, the datasets were divided as follows:

- EiMM[2]: this dataset was composed by *.xml* filed associated to each photos. In each *.xml* there were only two useful attributes, the Time of the Event and the SubClass of the Event. By the photo file it was extractable the PhotoID and the PhotoFormat.
- USED[1]: this dataset had extremely reduced annotations, the only attributes available were the PhotoID, the PhotoFormat and the SubClass of the Event(this last compressed in a *.txt* file for each SubClass).
- SED[3]: this dataset was annotated by a detailed *.xml* file thus the available attributes were the PhotoID, the PhotoFormat, the EventName, the SubClass of the Event, the Place of the Event, the Time of the Event and the Provenience URL of the Photo.

After this list of attributes for each dataset, it is possible to observe the heterogeneity described before and the, often, limited number of attributes available. Also the number of entities extractable from the input dataset are very sparse being in [1] [2] only the Event and the Photo, while in [3] were the Event, the Photo and the Provenience. As a direct result of the sparsity and limited number of the attributes of the limited entities, the number of queries that could be extracted from the input datasets were extremely limited either zero.

5.2 Output Datasets

The output datasets are an extremely enhanced version of the input datasets. First of all, now a discrete number of entities have been added and extended to the entire input datasets. The ER model in Figure 1 depicts entirely the entities added and in Section 2 they are fully described, but a short of the entities in the output dataset is: Photo, Event, Place, Organization, Person and Dataset. For each class, attributes have been added and filled as further described in Section 2 and finally they are now embedded in a single easy-to-use *.csv* file thus making the output datasets ready to be adopted for many different possible tasks (see 6). A complete list of the added attributes is: the Presence of people[13] in the Photo, the PriorClass of the Event, the DatasetURL, the PlaceURL of the Place, the PhotoURL of the Photo, all the attributes of the Dataset, all the attributes of the Organization and all the attributes of the Person part of the Organization. In table 3 a complete comparison of all the new attributes, instances and classes introduced during this work is performed.

[13] `https://github.com/UniTN-KDILab/Data-indexing-2018-19/tree/master/SCRIPTS/classify.m`

	Input Database	Output Database
People presence	✗	✓
Prior class	✗	✓
Sub class	✓	✓
Reference contact	✗	✓
Dataset URL	✓	✓
Organization URL	✗	✓
Place URL	✗	✓
Place name	✓	✓
Photo URL	✗	✓
Photo format	✓	✓
Time	✗	✓
Number of images	✗	✓
Number of attributes	✗	✓
Size in GB	✗	✓
First and Last name of reference	✗	✓
CSV files	✗	✓

Table 3: Comparative table for input and output databases structures.

As reported in Table 3, the innovations proposed in this work are useful to make the dataset search and query much more easier for the user. The heterogeneity found at the beginning of the process is now completely solved, such as the lack of information in some metadata. Then, another important feature to underline is the fact that with the new version of the datasets it is much easier to prepare data and make training of classifiers, such as neural networks, with a very large set of possible fields, not only in event recognition.

6 DB generation proposal

The output of this work aims to the generation of a proposal of a multi-field Event Database. Inspyred by the attribute addition, the normalization and the formal mapping proposed in this work, thus the pipeline followed from Section 1 to Section 5, the same methodology could be applied over many other Event datasets with the objective to generate a wide Event database that could be used in many Computer Vision tasks. In the same database, it should be possible to add single Photo instances with the possibility to generate an open-source database of events that could be used not only in the Computer Vision community, but also in many other research fields and non-research fields. In fact, being the database open-source, it could be used by regional and national authorities to extract statistics from the database giving a large number of information about the citizens behaviours. For example, if a mayor of a city would understand the amount of social activities and events provided by his government, he will only needs to consult our database and look at the social events percentages from the photos taken in his jurisdiction. Another illustrative example happens if the major or his sports assessor wants to know if the citizenship practice sufficient sport activities. In order to provide this type of information, our database could be consulted by asking the percentage of photos of sports events acquired in the local area. These are only few examples of the possible use of the database proposed here. What is sure is that events are the product of the society in a given area, and they provide a very wide and useful set of information and statistical data that can be used to enhance the life of people in a given area, to enhance the quality of the proposed events and, mainly, to facilitate the life of research groups when facing with the problem of datasets research for a given event/social task.

7 Final considerations and open issues

To conclude, a short resume of what was done for this project is written in Subsection (7.1) together with the main open issues found at the end of our work in Subsection (7.2).

7.1 Final considerations.

Our work was born to solve a common challenge in Media Indexing: the event datasets use, for training or statistics purposes. Therefore, a first research was performed to focus the attention on precise tasks to consider, in order to produce a valid method for doing data integration. Then, once the objectives were clearly defined, and thus the initial implicit queries, the datasets normalization has been defined for the input datasets in order to have a normalized structure and mapping among them. Through the use of *Protégé* it has been defined and proposed the PEI ontology (Section 2 and 3) over which the mapping of the input normalized data has been conducted by using the *Karma* toolkit.
Once the integration process was completed, an infinite number of queries are solvable and can be asked to the database. Some common examples have been proposed and reported in Section 4.
Finally, the final database proposal step took place starting from pipeline proposed in this work.

7.2 Open Issues

In conclusion, some open topics that are not considered in our work are here presented.
First of all, as written multiple times during the document, one of the main operations applied at the beginning was the reduction of the three input datasets ([1], [2], [3]) to make it possible to handle them in a reasonable time. Because of this process, the final output datasets proposed is only a small representative part of the original ones. Therefore, one open issue proposed by our team for future works is the expansion to the full input datasets, eventually by increasing the content adding some other datasets that are available in the literature.
Then, once the expansion task is completed, the second open issue depicted by our team is the retrieval and integration of the EXIF metadata in the Photo class. This probably will do the database desirable to forensics tasks filling completely the Photo attributes and making the output of the integration more robust and efficient to different uses and tasks.
In addition, one other critical point our team found is the completeness of the attributes part of the output database. In fact, we added to the ontology new attributes based on our actual knowledge of the problem from a Computer Vision view. For this reason, we suggest one additional analysis of the needing of the target users in order to better define the attributes (and classes) in the ontology taking into account the requirements of the task.
In addition, due to the excessive time demand of the attributes filling in the output *.csv* files, many fields are empty not for the attribute missing but for the time requirement to insert them in all the fields. Thus, an open issue leaved by our team is to fill all the attributes fields of the normalized *.csv* files. It is important to notice that this did not affect the output of this work being the objective a data integration pipeline among three different datasets which has been solved. One last aspect we noticed was the absence of the Event description. Unfortunately, in our output database Event captions are not present, because of the manual integration we had to do for the *Event* class and many other classes. Therefore, it is suggested to introduce, as future work, some automatic picture description

process(such as an image captioner), in order to provide at the end a short caption for each photo, which for our point of view could result really useful for the final users.

References

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