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Whose story is it anyway? Automatic extraction of accounts from news articles

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ABSTRACT

Narratives are comprised of stories that provide insight into social processes. To facilitate the analysis of narratives in a more efficient manner, natural language processing (NLP) methods have been employed in order to automatically extract information from textual sources, e.g., newspaper articles. Existing work on automatic narrative extraction, however, has ignored the nested character of narratives. In this work, we argue that a narrative may contain multiple accounts given by different actors. Each individual account provides insight into the beliefs and desires underpinning an actor's actions. We present a pipeline for automatically extracting accounts, consisting of NLP methods for: (1) named entity recognition, (2) event extraction, and (3) attribution extraction. Machine learning-based models for named entity recognition were trained based on a state-of-the-art neural network architecture for sequence labelling. For event extraction, we developed a hybrid approach combining the use of semantic role labelling tools, the FrameNet repository of semantic frames, and a lexicon of event nouns. Meanwhile, attribution extraction was addressed with the aid of a dependency parser and Levin's verb classes. To facilitate the development and evaluation of these methods, we constructed a new corpus of news articles, in which named entities, events and attributions have been manually marked up following a novel annotation scheme that covers over 20 event types relating to socio-economic phenomena. Evaluation results show that relative to a baseline method underpinned solely by semantic role labelling tools, our event extraction approach optimises recall by 12.22–14.20 percentage points (reaching as high as 92.60% on one data set). Meanwhile, the use of Levin's verb classes in attribution extraction obtains optimal performance in terms of F-score, outperforming a baseline method by 7.64–11.96 percentage points. Our proposed approach was applied on news articles focused on industrial regeneration cases. This facilitated the generation of accounts of events that are attributed to specific actors.

1. Introduction

Understanding social phenomena often involves the analysis of narratives, which can be "understood to organise a sequence of events into a whole so that the significance of each event can be understood through its relation to that whole" (Elliott, 2005). Narrative enters into the social sciences in two major ways. First, social scientists have theorised about the inherent narrative structure of social processes (Abbott, 1992; Abell, 2004) ranging from organisational change (Czarniawska et al., 1997) to the emergence of new professions (Abbott, 2014). Secondly, social actors make sense of the processes they engage in by developing

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accounts of the events they observe. Such accounts are performative in the process in which they occur (Tilly, 2004). Although narratives have been defined in multiple ways (Abbott, 2008; Elliott, 2005), ranging from compact to loose, there is a general understanding that they constitute a whole, in the sense of being constructed to convey some meaning (Abbott, 2008). The two ways in which narratives are relevant for understanding social processes come together in terms of the fact that narratives are frequently nested within other narratives. More specifically narratives may contain multiple accounts given by different actors or observers. Such accounts are prevalent especially in news articles, where reported events are commented on or reflected upon by different actors or outside observers. An *individual account*—an account provided by any one actor—is comprised of one or more attributions, i.e., statements or perceptions attributed to the actor. It is important to distinguish between individual accounts as it allows for taking into consideration the perspective of each actor, which in turn is helpful in narrative analysis (Trabasso & Nickels, 1992).

Social scientists have used text corpora, newspaper articles in particular, as a data source to study social processes, e.g., multi-party collaboration (Spekkink & Boons, 2015), conflict (Bearman, Moody, & Faris, 2002) and social mobilisation (Franzosi, 1999). These processes are constituted by social actors contesting each other's perspectives, and/or moving over time towards consensus on those perspectives. Identifying actor-specific perspectives is thus vital to facilitate this type of analysis.

Currently, a major challenge in the empirical study of social processes is the compilation of annotated textual data sets that can facilitate narrative analysis, which is costly in terms of manual effort and time. While natural language processing (NLP) methods have been employed in previous work (Sudhahar, Franzosi, & Cristianini, 2011) to support automatic compilation of such data sets, the nested character of narratives (i.e., the fact that a narrative often contains accounts of events according to different actors) has thus far not been given attention.

However, in using text corpora as a data source for understanding social processes, delineating between accounts given by different actors is crucial, as an individual account provides insight into the beliefs and desires which form the basis for the actions of a particular actor (Elster, 2007).

In this work, we aim to specifically address the problem of *nested narratives*: individual accounts of events provided by different actors, which are contained within a narrative. As the interpretation of events may vary from one "teller" to another (Andrews, 2002; Squire, 2002), it is crucial to delineate between individual accounts and to attribute them to their respective sources.

To this end, we propose an NLP approach which, to the best of our knowledge, is the first to address the automatic extraction of individual accounts from the text of newspaper articles. Casting the problem as a combination of a number of tasks, we have developed methods for named entity recognition, event extraction and attribution extraction. The resulting methods enabled the identification of different perspectives of multiple actors on any given event, thus making it possible to capture various interpretations of the event which may not always be in agreement or may even be conflicting.

The remainder of this paper is structured as follows: Section 2 presents a brief survey of previously reported work on narrative analysis as well as NLP methods that can facilitate it, while Section 3 describes the new annotated corpus that we have developed. In Section 4, we discuss details of our proposed methods, the results of which are then presented in Section 5, together with a number of observations. Finally, we share plans for future work and conclude the paper in Section 6.

2. Related work

Several methodologies for narrative analysis of social processes have been developed. Abell's work (Abell, 1984) provided algebraic rules for representing otherwise highly complex social processes in a more abstract manner. In the work of Bearman and Stovel (2000) and Bearman et al. (2002), narrative networks were generated based on the results of social network analysis. Meanwhile Czarniawska et al. (1997) as well as Fenton and Langley (2011) employed qualitative methods to explore the role of narratives in social life.

A number of efforts have also been undertaken to address the analysis of narratives in written news. Notable is the work by Sudhahar et al. (2011) which focused on the detection of key actors and their corresponding actions from crime-related New York Times news articles. Several papers focused on computational approaches to narrative analysis have also been published as part of the workshops on Computing News Storylines (CNewsStory 2015,2016), and the 2017 Events and Stories in the News Workshop (EventStory 2017). However, none of the previously reported work have considered the nested nature of narratives in news articles. To address this gap, our proposed approach integrates event extraction with attribution extraction, in order to identify individual accounts of events from news articles. With respect to the extraction of events, our work is distinct from approaches such as that of Yang, Shi, and Wei (2009), which defined an event as a set of news stories. Much more similar to our work are approaches that defined events in a finer-grained manner, i.e., as structured representations that encapsulate the entities involved in events as well as the verbs or nouns that signify them. Specific examples of such work include those that build upon semantic role labelling (Rospocher et al., 2016; Spiliopoulou, Hovy, & Mitamura, 2017). However, our proposed approach explores additional techniques for optimising the results of semantic role labelling tools.

Relevant work in terms of attribution extraction include the work of O'Keefe, Pareti, Curran, Koprinska, and Honnibal (2012) and Pareti, O'Keefe, Konstas, Curran, and Koprinska (2013) for extracting and attributing quotations. Their work handled the attribution of direct and indirect speech (i.e., who-said-what), but not the identification of other ways by which an actor may reflect or share his perceptions on news events, e.g., through thoughts, beliefs, desires, which also form an important part of individual accounts. Although the open information extraction system MinIE (Gashteovski, Gemulla, & Del Corro, 2017) sought to extract perceptions, it relied heavily on the detection of subordinate clauses (e.g., *Mr Livingstone believes [that Londoners will pay extra council tax]*). This, however, would fail on many cases, specifically on sentences containing direct quotations, e.g., *He praises Merci: ["It's practical, it works"]*. Our approach, meanwhile, attempts to extract attribution of all of direct and indirect speech, and perceptions.

Although annotated news corpora exist, e.g., ACE2005 (Walker, 2006), MEANTIME (Minard et al., 2016) and EventStoryLine (Caselli & Vossen, 2017), none have incorporated attribution annotation. Meanwhile, the Penn Discourse Treebank 2.0 (PDTB) corpus of Wall Street Journal news articles contains attribution annotation but not event annotations (Prasad et al., 2008). Hence, to support the development and evaluation of our proposed methods, a corpus of news articles was constructed and enriched with event and attribution annotations, as described in the next section.

3. Corpus development

In this section, we describe the construction of a new annotated corpus of newspaper articles containing information on processes of industrial regeneration. Such processes can be defined as the emergent and designed re-establishment of economic activities in geographical areas that previously were industrial sites but which had gone into decline. Regeneration is a complex longitudinal process (taking at least five years) where individual social actors such as firms, knowledge institutes, governmental authorities, labour unions and non-governmental organisations (NGOs) interact to generate new economic activities and the infrastructure required for those activities.

In this work, we are interested in obtaining evidence of industrial regeneration in the area of Greater Manchester in the UK, traditionally an area with bustling industrial activity, which had gone into decline since the early 1970s (Mason, 1980). Within this wider region, several projects have been initiated that constitute regeneration. In the following, we describe three of such projects (which we also refer to as cases) and explain our rationale for selecting them as the topic areas of our corpus.

- Commonwealth Games: hosted by Manchester in 2002, requiring an investment in building the necessary infrastructure that at the same time was intended to help regenerate East Manchester, a deprived area.
- MediaCityUK: a media cluster that emerged when a decision was made in 2004 to move a substantial portion of the activities of the British Broadcasting Corporation (BBC) to Salford Quays, the former dockyards in Greater Manchester that closed in 1982.
- Metrolink: a public transport network designed to connect parts of Greater Manchester, which has undergone extensions in several phases since 1992.

These projects were selected in order to provide distinct processes of regeneration. The Commonwealth Games signalled the organisation of a major event that was intended to catalyse regeneration, while the MediaCityUK case focused on negotiations between the BBC and the national government to relocate economic activities to an area in decline. Meanwhile, the Metrolink case centred on the extension of existing infrastructure and delivery of related services that were expected to facilitate economic activity in the areas that became connected; this case is also characterised by temporary loss of services due to building the extensions. Based on this distinctiveness across the three different projects, we expect to see varying frequencies of named entities and event types (as specified in our annotation scheme, described below).

The remainder of this section presents our strategy for selecting documents and details of the annotation effort: the annotation scheme and guidelines that were developed, the annotation procedure, and the resulting annotated corpus.

3.1. Document selection

For all of the three cases described above, articles published in UK newspapers were retrieved using the LexisNexis library.[1] Below is a description of the query that was specified for retrieving articles for each case. The articles that were finally selected for inclusion in the corpus were limited to certain time spans.

- Commonwealth Games: “Manchester” AND “Commonwealth Games” were used as key words for searching. Only articles published in 2001 and 2003 were included in order to avoid those reporting the sports events themselves.
- MediaCityUK: “BBC” AND “Salford Quays” and “MediaCity” were used as a search key words. Articles from an early phase of its development (from 2004 to 2006) were selected, covering the decision-making of the BBC in relation to local and national governmental agencies promoting the move.
- Metrolink: “Metrolink” was used as search key word. Articles published between 2008 and 2010 were selected, covering a phase where extensions to the original tram network were created towards MediaCity, Droylsden and Rochdale. To avoid any overlap with the second case we excluded articles mentioning MediaCity.

Through the above steps, a total of 25 news articles were included in the corpus: eleven in the Commonwealth Games subset (henceforth referred to as Games for brevity), seven in the MediaCityUK subset, and another seven in the Metrolink subset.

3.2. Annotation scheme

To clearly specify how the news articles in our corpus should be annotated, we developed a scheme that is intended to capture information on events and the entities that participate in them. Importantly, attributions (i.e., speech, thoughts, beliefs and desires,

[1] https://www.lexisnexis.com/uk/legal/ .

Table 1
Types of named entities covered by the annotation scheme.

Entity Type	Description
Place_or_region	A specific place (e.g., "Stockport") or region (e.g., "North West England").
Person_or_people	A specific person (e.g., "Mayor Andy Burnham") or a group of people (e.g., "residents of Salford")
Organisation	A group of people acting coherently, e.g., an institute, firm, company or team, a division of the government (e.g., "Manchester City Council"), or a non-governmental organisation
Infrastructure	Entities that are created, usually on purpose, to make possible the performance of some activity, e.g., "Manchester City Stadium"
Artefact	A product, tangible (e.g., "Android mobile device") or otherwise (e.g., "benefits").
Financial_resource	Monetary capital which is provided by some agent and made available to some other agent(s) for making activities possible (e.g., "grants")
Numerical_expression	A numerical value such as a monetary amount (e.g., "3 million pounds").
Time_expression	A temporal expression that refers to a point in time (e.g., "September2017")

together with their corresponding source entities) need to be captured in order to identify individual accounts pertaining to the process of regeneration.

The following annotation tasks were thus defined, each designed to capture a different type of information.

- Entity annotation: the mark-up of mentions of entities which are (potentially) involved or participating in events. The annotation scheme covers the types presented in Table 1. In addition, a Coreferring_expression type can be used by an annotator in cases where an entity is denoted by an anaphoric expression (e.g., a pronoun).
- Event annotation: concerned with the annotation of any event, i.e., an occurring interaction, activity or process, denoted by a word or phrase (referred to as a *trigger*) typically consisting of a verb (e.g., "delivered"), its nominalisation (e.g., "delivery") or a noun (e.g., "launch"). In the case of named events, e.g., "Commonwealth Games", the name itself serves as the trigger. Any number of entities, i.e., *participants*, may be involved in an event, each of which plays a specific role. For example, an entity that is being affected or acted upon in an event is a *subject*, while one that drives or initiates an event is an *agent*. Importantly, information specifying *when* and *where* an event occurs may also be available. If an event is described as something that did not happen at all, it is considered as a *negated* event. In Table 2 is a listing of our event types of interest, which are all relevant to industrial regeneration processes.
- Attribution annotation: a type of annotation focused on marking up speech (i.e., direct and indirect quotations), thoughts, beliefs and desires, which are then linked to the actors and observers who provided them. We note that to simplify this task for our annotators, attribution was annotated just like an event. The Articulation event type (cf. Table 2) was used specifically for this purpose, where subject is the speech, thought, belief or desire that has been expressed in the article, and agent is its source entity.

Our annotation guidelines document in detail the scope of each of the annotation types above. Importantly, they also provide instructions on what needs to be marked up in text for each of these annotation types, as well as conventions that annotators are encouraged to follow in order to enhance consistency.

3.3. Annotation procedure

The annotation of news articles was carried out by two annotators. The first annotator is an economic sociologist with a strong expertise in the regional dynamics of innovation and regeneration. He led the development of the annotation scheme, identifying the entity and event types that are of relevance to industrial regeneration. The second annotator is a PhD student whose work focuses on developing tools for analysing regional sustainable industrial regeneration based on principles of circular economy. Table 3 presents the number of news articles annotated by each of the annotators for each of the three subsets. To allow us to measure inter-annotator agreement (IAA), some articles were annotated by both of them, albeit independently.

All of the annotation tasks were carried out using the brat rapid annotation tool (Stenetorp et al., 2012). After configuring the tool based on our annotation scheme, each of the annotators was trained on its use. They carried out their annotations over the span of a

Table 2
Types of events covered by the annotation scheme.

Event types		
Birth	Realisation	Death
Movement	Progress	Revival
Emigration	Status_quo	Investment
Immigration	Production_or_consumption	Organisation_change
Support_or_facilitation	Participation	Organisation_merge
Protest	Transformation	Collaboration
Planning	Knowledge_acquisition	Competition
Decision	Decline	Articulation

Table 3
Number of annotated news articles. The last column indicates the number of articles that were annotated by both annotators.

	Annotator 1	Annotator 2	#Overlapping
Games	11	0	0
MediaCityUK	5	5	3
Metrolink	5	5	3

month. Fig. 1 shows a portion of an annotated article as visualised in brat.

Discussions were held whenever questions or issues were raised by either annotator. If their doubts resulted from instructions or descriptions that were ambiguous or not well illustrated, we updated the annotation guidelines to introduce clarifications and further examples.

3.4. Annotation results

As described above, some of the news articles in the corpus were annotated by both annotators, enabling us to measure inter-annotator agreement (IAA). Specifically, three articles in each of the MediaCityUK and Metrolink subsets were annotated by both annotators. IAA was measured by calculating F-score, treating the annotations from Annotator 1 as gold standard and those from Annotator 2 as response. In this manner, on the MediaCity and Metrolink subset, IAA was determined to be 0.52 and 0.60, respectively.

Table 4provides the number of annotations in the resulting corpus, segregated into subsets corresponding to our three cases. We note that in our proposed methodology, described in the next section, we utilised the Games subset as our development data set. The two other subsets, MediaCityUK and Metrolink, were set aside and were used purely for evaluation only, the results of which are presented in Section 5.

4. Methods

A narrative can contain any number of accounts provided by one or more actors or observers. We thus posit that the analysis of a narrative in textual form, e.g., a news article, should consider such nested structure of narratives. To this end we defined and carried out the NLP tasks described below, aimed at the extraction of attributions—which comprise individual accounts—and the events that they contain.

4.1. Named entity recognition

As a first step towards the automatic extraction of events from text, entities that are potentially involved in them were marked up

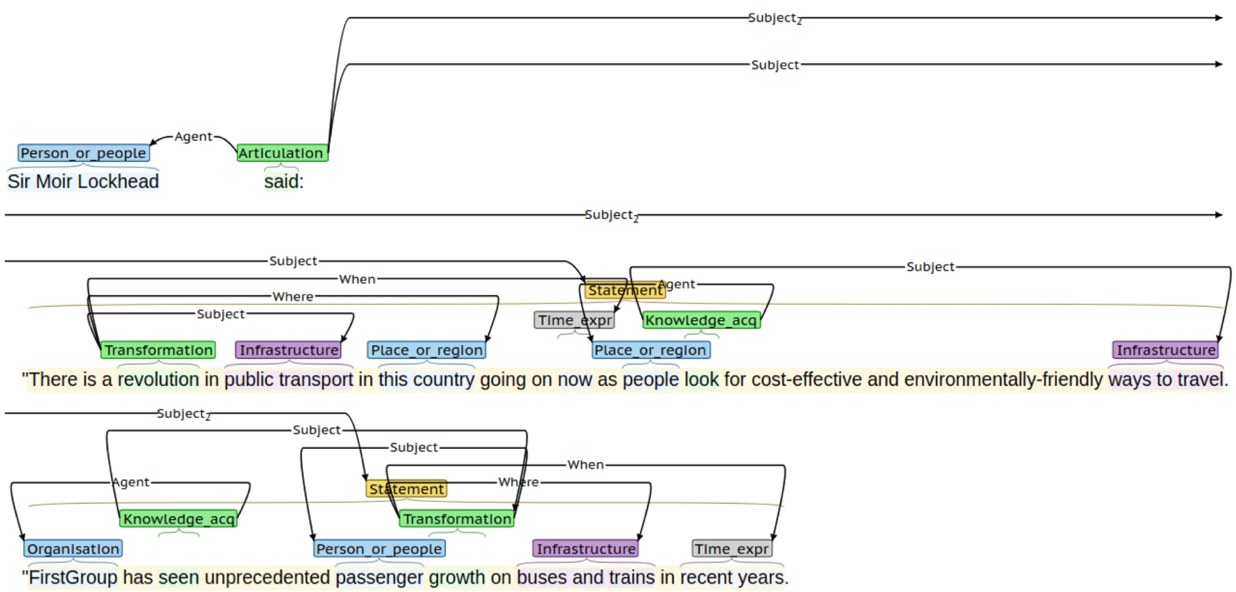

Fig. 1. Sample news article annotated using the brat tool. The Articulation event type captures attribution. We note that its subject (the speech, thought or desire being expressed) may contain events within, e.g., the Transformation and Knowledge_acquisition events shown.

Table 4
Characteristics of the resulting annotated corpus. The second column indicates the total number of unique articles in each subset, and the average article length in terms of number of tokens (in brackets).

	#Articles (#Tokens)	#Entities	#Events	#Attribution
Games	11 (384)	389	441	84
MediaCityUK	7 (536)	473	424	130
Metrolink	7 (352)	342	301	54
ALL	25 (418)	1204	1166	268

Table 5
Mappings of named entity types.

Source corpus	Source type	Target type
ACE2005	Location	Place_or_region
	Geo-political entity	Place_or_region
	Person	Person_or_people
	Organisation	Organisation
	Facility	Infrastructure
	Money	Financial_resource
	Numeric value	Numerical_expression
	Timex	Time_expression
	Weapon	Artefact
	Vehicle	Artefact
DFKI	Product	Artefact

using a machine learning-based named entity recognition (NER) tool. Specifically, we employed the artificial neural network-based NeuroNER (Dernoncourt, Lee, & Szolovits, 2017) to build a sequence labelling model. This package was chosen as it implements the state-of-the-art approach to NER, which combines long short-term memory (LSTM) and conditional random field (CRF) models (Lample, Ballesteros, Subramanian, Kawakami, & Dyer, 2016). In developing our own models, we utilised two data sets as sources of labelled training samples. First is the 2005 Automatic Content Extraction (ACE2005) corpus (Walker, 2006) consisting of a total of 599 newswire and weblog documents in which the following named entity types were annotated: Person, Location, Organisation, Geo-political entity, Facility, Weapon and Vehicle. The second data set is the DFKI-LT corpus of 152 webpages enriched with annotations of business product names (Schön, Mironova, Gabryszak, & Hennig, 2018). Two NER models were trained, one on each of the ACE2005 and DFKI-LT data sets. Table 5 shows how the entity types recognised by these models were mapped to our own entity types.

4.2. Event extraction

After training our NER models, we developed a method for event extraction based upon semantic role labelling (SRL): the task of identifying arguments of predicates in a given sentence (Jurafsky & Martin., 2009). Importantly, SRL is also concerned with determining the role of each argument, according to what is defined in a predicate's semantic frame, i.e., a structured representation of background knowledge specifying the various elements that comprises a concept. For example, the concept of asking someone to carry out an action can be represented by a Request frame[2] encapsulating elements pertaining to the source of the request, the addressee to whom the request is directed, its content and the channel for communicating it.

We now outline the steps that were taken in the way of developing our event extraction approach mostly based on the application of existing semantic role labelling tools and resources.

4.2.1. Ensemble of semantic role labelling tools

Two semantic role labelling tools were investigated. The first one is the Semantic Analyzer of Frame Representation (Semafor), an open-source parser that extracts predicates and their corresponding semantic arguments (Das, Chen, Martins, Schneider, & Smith, 2014). Underpinned by statistical models, Semafor identifies such semantic predicate-argument structures following FrameNet, a manually curated computational lexicon that catalogues thousands of semantic frames (Baker, Fillmore, & Lowe, 1998). In FrameNet, each semantic frame is represented by predicates (referred to as lexical units), i.e., words such as verbs or nouns that evoke it, together with frame elements—entities playing specific roles that contribute to the meaning of the frame, e.g., Speaker, Addressee, Message and Medium in the case of the Request frame. The second tool is a deep learning-based semantic role labelling (Deep SRL) model (He, Lee, Lewis, & Zettlemoyer, 2017) which identifies the arguments of predicates—restricted to verbs only—following the roles defined in Proposition Bank (PropBank) (Palmer, Gildea, & Kingsbury, 2005).

[2] https://framenet.icsi.berkeley.edu/fndrupal/frameIndex .

Upon assessing the outputs produced by each tool on documents in our development set, we observed that DeepSRL is able to identify predicates and arguments better than Semafor. Nevertheless, unlike DeepSRL, Semafor assigns semantic categories—in the form of semantic frame names—to the predicates that it identifies, which are useful for predicting event types. We thus formed an ensemble of the two SRL tools by combining their outputs. Firstly, all of the predicates identified by DeepSRL are kept (and given the generic label "Event" as their default semantic frame name), together with their corresponding arguments. Where the same predicate was identified by both tools, the semantic frame name provided by Semafor is applied to the frame identified by DeepSRL. The rest of the predicates extracted by Semafor are discarded.

4.2.2. Mapping of FrameNet frames to event types

As described in the previous section, in this work we are interested in events pertaining to industrial regeneration. A step was thus introduced in order to limit the semantic frames returned by the ensemble SRL tool to event types of interest.

Mappings between semantic frames and event types covered by our annotation scheme were derived automatically based on the gold standard annotations in the documents in our development set. Firstly, the ensemble SRL tool was applied on these documents. We then recorded the name of the semantic frame identified by the tool for every predicate that coincided with a gold standard event trigger. Alongside each identified semantic frame name, we indicated the gold standard event type associated with the event trigger. For instance, in one of the documents in our development set, the verb "agreeing" was given the label Make_agreement_on_action by the ensemble SRL. According to the gold standard annotations for that document, the same verb is the trigger of an event of type Decision. Thus a mapping is created between Make_agreement_on_action and the Decision event type. Any semantic frame that appears to correspond to multiple event types is mapped to the generic event type Event.

The derived mappings were used in discarding any semantic frames identified by the ensemble SRL tool, that did not correspond to any event type of interest. The remaining semantic frames were considered as events, with predicates serving as event triggers. Named entities (recognised by our NER models) within the span of semantic arguments identified by the ensemble SRL tool, were then treated as event participants.

4.2.3. Filtering

A semantic frame may be evoked by any number of predicates or lexical units. Hence, by virtue of the frame-event type mapping described above, potentially many predicates—including irrelevant ones—may become associated with a particular event type. For example, based on the mapping step above, the Request semantic frame was mapped to the Decision event type based on the fact that the verb "order" was manually annotated in our corpus as a gold standard trigger for a Decision event, and that the ensemble SRL tool assigned it the Request semantic frame name. There is thus a danger that any predicates that are assigned the Request semantic frame name by the ensemble SRL will be considered as triggers of Decision events. This may not be ideal as there are many other lexical units that may evoke the Request frame, including "appeal", "beg" and "invite", which do not necessarily pertain to Decision events.

To mitigate this issue, a filtering step was introduced. This is based on the compilation of a look-up list of predicates—together with the semantic frames identified by the ensemble SRL—that include only frames of interest derived from our development corpus, and categorised by the corresponding part-of-speech tags of gold standard triggers. Continuing from the example above, as the noun "appeal", for instance, was not annotated as a Decision event trigger in the development corpus (and hence will not appear in our look-up list), it will be discarded by this filtering step even if the ensemble SRL assigns it the Request semantic frame name.

4.2.4. Expansion of mappings based on related frames

To enhance the applicability of our semantic frame-event type mappings, we sought to expand them by taking into consideration other related semantic frames. To this end, we leveraged the graph of frame relations in FrameNet. Specifically, for every semantic frame included in our mappings, the FrameNet graph was searched for frames that are related by inheritance, i.e., child and parent frames. For example, according to the FrameNet graph of frame relations, the Make_compromise frame—which as we showed above was mapped to the Decision event type—is a child of the Make_agreement_on_action frame. Therefore a new mapping between Make_compromise and Decision was added to our list of mappings. This implies that any predicates (e.g., the verb "compromise") that will be assigned the Make_compromise semantic frame name by our ensemble SRL will now be identified as a trigger for a Decision type of event.

This step increased the number of semantic frame-event type mappings from 141 to 500. We prepared versions of our event extraction approach with and without such expansion of our mappings.

4.2.5. Matching of event nouns

The event triggers identified by our approach so far are constrained to predicates catalogued in FrameNet and PropBank (due to the fact that the tools that constitute our ensemble SRL are informed by these two computational lexica). Seeking to increase our coverage, especially with respect to named events, an event noun lexicon was compiled. Specifically, noun event triggers that are annotated in three corpora containing gold standard event annotations, i.e., ACE2005, TimeBank (Pustejovsky et al., 2003) and NewsReader (Minard et al., 2016), were automatically collected. Containing 984 unique nouns, the resulting lexicon includes not only nominalised verbs but also words which tend to appear as head nouns of named events, e.g., "game" in "Commonwealth Games", "forum" in "North West Tourism Forum". Input text was then matched against this lexicon in order to extract more event triggers, including those which form part of named events. In evaluating our approach, we observed the effect of including or excluding the use of this event noun lexicon for trigger matching.

Table 6
Summary of event extraction results. Check marks indicate which components have been incorporated into that version of our approach. The version that does not include any of the three components corresponds to our baseline approach.

Subset	Filtering	Graph	Lexicon	Precision	Recall	F-score
Commonwealth Games (5-fold cross validation)				0.3788	0.7590	0.5054
	✓			**0.4506**	0.7144	**0.5526**
		✓		0.3424	0.7880	0.4774
			✓	0.3384	0.8692	0.4871
	✓	✓		0.4130	0.7424	0.5307
	✓		✓	0.3818	0.8486	0.5267
		✓	✓	0.3156	**0.8812**	0.4648
	✓	✓	✓	0.3624	0.8594	0.5098
MediaCityUK				0.2920	0.7650	0.4227
	✓			**0.3250**	0.7120	0.4463
		✓		0.2790	0.8680	0.4223
			✓	0.2780	0.8770	0.4222
	✓	✓		0.3080	0.7980	0.4445
	✓		✓	0.3120	0.8720	**0.4596**
		✓	✓	0.2570	**0.8930**	0.3991
	✓	✓	✓	0.2910	0.8850	0.4380
Metrolink				0.3600	0.7840	0.4934
	✓			**0.3810**	0.7110	0.4961
		✓		0.3240	0.8380	0.4673
			✓	0.3400	0.9020	0.4938
	✓	✓		0.3620	0.7550	0.4894
	✓		✓	0.3670	0.8870	**0.5192**
		✓	✓	0.3140	**0.9260**	0.3991
	✓	✓	✓	0.3560	0.8970	0.5097

4.3. Attribution extraction

Authors of narratives make use of attribution to indicate “who expressed what”, where *what* pertains to a quotation or perception, and *who* denotes its original source. The kind of information that is more commonly attributed is speech (i.e., something that was said), which can be direct (e.g., *He said, “She will deny it.”*) or indirect (e.g., He said that she will deny it.). However, other kinds of information may also be attributed (Prasad, Dinesh, Lee, Joshi, & Webber, 2006), such as beliefs (e.g., He expects that she will deny it.) in which verbs other than those for reporting (e.g., “said”, “announce”, “mention”) may be used.

In this work, we consider all forms of attribution as components of individual accounts, which as described earlier, constitute narratives. We thus aim to automatically extract attribution information, i.e., any direct or indirect speech, thoughts or beliefs, together with its corresponding source entity. This will then be represented as an event of type Articulation (cf. Section 3), with the speech, thought or belief as subject and the source entity as agent.

The ensemble SRL tool described above is capable of extracting attribution involving speech. However, as the underpinning tools and lexica do not take into account frames that convey thoughts and beliefs, we developed a method for also capturing this kind of attribution. Firstly, a lexicon of attribution verbs was compiled, drawn from the following verb classes defined by Levin (1993): “advise”, “assessment”, “characterize”, “communication”, “conjecture”, “correspond”, “declare”, “judgement”, “learn”, “long”, “manner of speaking”, “see”, “sight” and “want”.

In addition, verb lexical units that evoke the Statement frame in FrameNet as well as the frames inheriting from it (Affirm_or_deny, Complaining, Predicting, Reading_aloud, Recording, Reveal_secret, Telling) were incorporated into the list.

The resulting lexicon, containing a total of 609 unique verbs, was then utilised as a look-up list to detect whether any of the sentences in a news article conveys attribution.

If a sentence contains a matching verb, the dependency parse tree of the sentence (provided by the Enju parser (Miyao & Tsujii, 2008)) is checked to determine whether the verb is succeeded by a *that*-clause, which typically follows verbs of attribution. If this is the case, a new Articulation event is instantiated, with the verb as its event trigger and its first and second syntactic arguments as its agent and subject, respectively.

In the succeeding section, we report the results that we obtained upon evaluating our proposed methods.

5. Results and discussion

We assessed the effectiveness of our approach (i.e., pipeline) by evaluating various versions of it where certain components (as described above) have been included or excluded.

5.1. Event extraction

In our evaluation of event extraction, summarised in Table 6, we considered as our baseline approach the ensemble SRL tool (Section 4.2.1) enhanced by frame-event mappings (Section 4.2.2). We then investigated the impact on performance of each of the following components: filtering (Section 4.2.3), graph-based mapping expansion (Section 4.2.4), and matching against the event noun lexicon (Section 4.2.5). Standard metrics of precision, recall and *F*-score were used in evaluating the extent to which our pipeline is able to identify events correctly (based on matched triggers). The evaluation was carried out on each of the three subsets. For the Games subset, the metrics were calculated according to the results of 5-fold cross-validation. Meanwhile, versions of the pipeline evaluated on the MediaCityUK and Metrolink subsets were developed based on all of the documents in the Games subset.

As can be observed in Table 6, the introduction of the filtering component consistently leads to enhanced precision. For each of the three subsets, extending the baseline approach with the filtering component boosts precision by 3–7 percentage points. This is unsurprising as the filtering component is meant to discard predicates that are irrelevant to our event types of interest. Meanwhile, each of the graph-based mapping expansion and the matching of predicates against our event noun lexicon leads to improved recall. Upon extending the baseline approach with the graph-based expansion of frame-event mappings, improvement in recall ranging from 3 to 10 percentage points can be obtained across the subsets. Extending it with matching of predicates against the event noun lexicon leads to even more noticeable improvement, i.e., 10–11 percentage points. Again this is not surprising as these two components are meant to capture more event triggers. It is worth noting that despite the significant improvements in recall, precision was not harmed substantially by each of these components, i.e., only a 2–4 percentage-point decrease.

When comparing pipelines incorporating various combinations of the three components discussed above, it becomes clear that optimal precision is consistently obtained when only the filtering component is added to the baseline. For optimal recall, however, the pipeline that makes use of both graph-based mapping expansion and event noun lexicon is most suitable, obtaining 88.12 to 92.60% across the corpus subsets.

It is, however, the pipeline that incorporates filtering and makes use of the event noun lexicon, which obtains optimal F-score, based on the evaluation data set (45.96 and 51.92% on the MediaCityUK and Metrolink subsets, respectively).

Out of the eight versions of the pipeline, we selected as our final solution the one that obtains optimal recall, where the graph-based mapping expansion and event noun lexicon have been integrated with the baseline. This is because within the context of supporting the compilation of data sets in support of narrative analysis by social scientists (as discussed in Section 1), optimal recall is more preferable in that it minimises their effort in terms of creating new annotations. That is, it is more acceptable to deal with sub-optimal precision and remove noise (i.e., false positives), than to check for missed events (i.e., false negatives) that then need to be manually created.

5.2. Attribution extraction

We evaluated each of our two proposed approaches to attribution extraction and compared their performance with that of a baseline system, i.e., a state-of-the-art open information extraction tool, MinIE.[3] The first approach is the event extraction pipeline corresponding to our final, high-recall solution, while the second is our verb class lexicon-based attribution extraction method, as described in Section 4.3. The results of performance evaluation are presented in Table 7. The event extraction pipeline consistently obtained optimal recall relative to MinIE, by a margin of 19.05, 19 and 21.01 percentage points on the Commonwealth Games, MediaCityUK and Metrolink subsets, respectively. It is, however, worth noting that in terms of F-score, our verb class lexicon-based attribution extraction method consistently obtained superior performance. Specifically, it outperformed MinIE by 10.92, 11.96 and 7.64 percentage points, and the event extraction pipeline by 2.01, 7.19 and 8.51 percentage points on the Commonwealth Games, MediaCityUK and Metrolink subsets, respectively. It is noticeable that, relative to the Commonwealth Games and Metrolink subsets, inferior performance was obtained on the MediaCityUK subset. Our error analysis showed that this can be explained by a greater number of verbs that were marked up as trigger words for Articulation events in the gold standard annotations, that were not covered by our lexicon of attribution verbs. These include verbs such as “demand”, “expect”, “fear”, “recall” and “threaten”, which do not appear in any of Levin’s verb classes that were identified as relevant to attribution. In applying our proposed method on any other corpora, our lexicon can be augmented to include all Articulation trigger words in our corpus.

5.3. Towards narrative analysis

As mentioned in Section 1, it is crucial to delineate between accounts provided by different actors and observers. Fig. 2 presents sample attribution extraction results that allow for the identification of varying perspectives on the same Decision event: the licence fee settlement (i.e., the government agreeing to the licence fee increase that the BBC proposed as part of their move to Manchester). The three boxes in the figure show statements attributed to the BBC Director General (Mark Thompson), Manchester City Councillor (Sir Richard Leese) and Euro-MP for North West England (Arlene McCarthy), respectively. The BBC Director General clearly considered an unfavourable licence fee settlement as a deal-breaker for the BBC’s move to Salford in Manchester (Box 1). Councillor Sir Richard Leese viewed the settlement in a completely different way, stating that the move is not contingent on it (Box 2). However, this view was not shared by the Euro-MP for North West England, who recognised that the BBC move is dependent on the licence fee

[3] https://gkiril.github.io/minie .

Table 7
Attribution extraction results.

Subset	Approach	Precision	Recall	F-score
Commonwealth Games	MinIE	0.7027	0.6190	0.6582
	Ensemble SRL + Graph + Lexicon	0.6939	**0.8095**	0.7473
	Levin's verb classes	**0.7500**	0.7857	**0.7674**
MediaCityUK	MinIE	0.4884	0.5000	0.4941
	Ensemble SRL + Graph + Lexicon	0.4460	**0.6900**	0.5418
	Levin's verb classes	**0.5870**	0.6429	**0.6137**
Metrolink	MinIE	**0.7333**	0.5789	0.6470
	Ensemble SRL + Graph + Lexicon	0.5360	0.7890	0.6383
	Levin's verb classes	0.6071	**0.8947**	**0.7234**

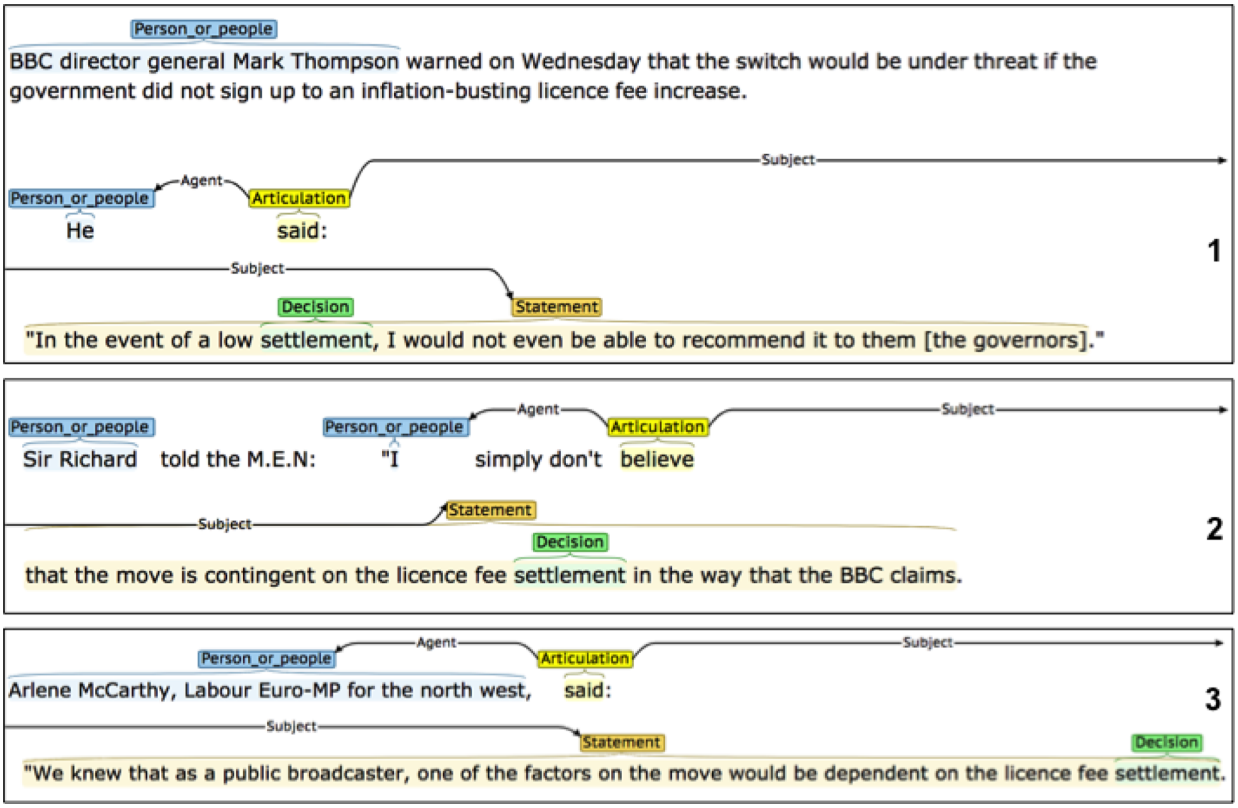

Fig. 2. Sample attribution extraction results identifying varying perspectives on the same Decision event. News article source: "BBC move 'crucial' to us all, says city chief" by David Ottewell, Manchester Evening News, 13 October 2006.

settlement (Box 3). We observe from this example that the three Articulations assign different consequences to the same event, highlighting a diversity in perspectives that can be expected to influence the process under study.

These results, together with those presented in the previous sections, demonstrate that our proposed approach can feasibly identify events and attributions (which constitute individual accounts). We discuss next the value of automating such tasks in the way of facilitating narrative analysis.

Events described in accounts of actors involved in processes can be considered as part of the main narrative or story line. In one of the news articles in the Metrolink case, for example, an actor announced the way financial resources will be allocated: *Transport Secretary Ruth Kelly this week announced the money would go to the city as part of a charging scheme to cut congestion.* The event (of allocating the money to the city) belongs to the main narrative of the article.

In other cases, however, events mentioned in an article belong to accounts provided by observers (rather than the story line), who reflect on the events that are occurring. In the case of the Commonwealth Games, for instance, one article presents accounts of residents about regeneration in the area around the main Stadium. Speaking of the situation prior to the Games, a line in the article reads: *"They do not care who they put into the houses - they just want the money," she says.* This statement contains events that when viewed outside of an account of an observer, would lead to include them in the story line, while they are instead beliefs of one observer, i.e., a resident.

In the same article, another resident articulates her view on the building of new homes in the area. The following excerpt captures part of her reflections: *Barbara, who is 55, says the only cloud on the horizon is that an awful lot of homes are being demolished in east Manchester in order to attract new people to the area.* Here there is a clear opinion expressed regarding the demolition events.

The MediaCityUK case contains a part of the process in which the BBC and the national government are negotiating about the conditions for the former to move to Salford. As part of the negotiations, in one newspaper article, statements of the BBC Director General are presented along with those of MPs. The article contains the following line: They [representatives of Salford] are likely to leave any lobbying to MPs, who will argue that it is the BBC itself which has pointed out the importance of reconnecting with their audience and creating a number of jobs.

This statement contains a sequence of events (the move to Salford as a way to create jobs and to reconnect with audiences), which is articulated to counter the sequence of events presented by the BBC Director General, who articulates that the move may not be the best way to achieve those goals. Here, the contradicting statements cannot be both taken as containing factual events. Rather, they should be considered as accounts of actors in a negotiation (where such challenging of positions and articulated beliefs is common).

6. Conclusion and future work

In this paper we described our work on extracting events and the accounts containing them, from news articles. Methods for event and attribution extraction were developed and evaluated based on a new corpus of news articles in which industrial regeneration events have been annotated.[4] Results show that our proposed methods that leverage resources such as FrameNet and Levin's verb classes, obtain optimal recall without substantially harming precision.

As illustrated in the examples presented in the previous section, accounts—and the events they contain—can be further categorised in support of narrative analysis. Firstly, depending on the source of an individual account, events can be categorised as being part of the main narrative or not. Specifically, events described by actors belong to the main narrative, while those remarked upon by observers do not. Such categorisation can be cast as a machine learning task, whereby contextual information on the entities who provided accounts (source entities) may be used as features for classification. Accounts can also be analysed to detect whether they contain any opinions. This can be considered as an affect analysis task, where sentiments or emotions of source entities towards events are detected (Ptaszynski et al., 2013). Moreover, accounts (and events therein) may be automatically analysed for their factuality. Some accounts, for example, may convey beliefs, desires or expectations, rather than factual events. Such analysis can be facilitated by speculation detection (Qian et al., 2016) or future reference extraction (Nakajima, Ptaszynski, Honma, & Masui, 2016; 2018). Furthermore, contradicting statements might be articulated regarding a given event, which can only be detected upon the identification of textual mentions pertaining to the same event, i.e., co-referring events. This task, known as event coreference resolution (Lu & Ng, 2018), builds upon entity coreference resolution as well as entity normalisation or linking (Mihalcea & Csomai, 2007). In our future work, we intend to undertake these tasks as further steps towards narrative analysis.

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