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# Modelling creative influence between artists and their works with OWL and CIDOC CRM

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**Abstract:** In this paper we present an ontology for modelling creative influence between artists as documented as part of an international art exhibition on Dutch Golden Age genre painters titled *Vermeer and the Masters of Genre Painting: Inspiration and Rivalry*. The model, which describes influences on an artwork-to-artwork level, was developed in close cooperation with the curatorial advisory board of the exhibition and has guided the data gathering efforts in preparation for the exhibition. Our ontology extends the CIDOC Conceptual Reference Model (CRM) and has been influenced in its design by the CRM. It was implemented using the Erlangen CRM implementation and populated with an RDF graph containing over 900 instances of individual connections between works of art, referencing external Linked Open Data from Getty ULAN. The focus of this paper is on technical questions of knowledge modelling and implementation. The wider project context, the genesis of the domain expert conceptualizations and use cases for the ontology and RDF data are presented elsewhere in greater detail.

**Keywords:** Artistic influence/inspiration, OWL/RDF ontology, CIDOC Conceptual Reference Model, Erlangen CRM, Linked Open Data (Getty ULAN)

## 1 Introduction

Masters of the Dutch Golden Age have long been known for taking inspiration from each other and incorporating elements or techniques seen elsewhere – albeit often modified – into their own paintings. The exhibition project *Vermeer and the Masters of Genre Painting: Inspiration and Rivalry* on display successively at the Musée du Louvre, Paris, the National Gallery of Ireland, Dublin, and the National Gallery of Art, Washington, throughout 2017 and early 2018 focuses on mutual inspiration taking between preeminent Dutch genre painters in the period from 1650 to 1675 [Wa17]. As part of the exhibition project several data sets on artist relations and artist whereabouts were compiled by art historians, mostly from the literature. The core set of these data gathering efforts covers observations on pairs of artworks each expressing an hypothesis that one work of art was inspired by the other. In this paper we present the data model according to which this data set was recorded and

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implemented as linked data. The focus of this paper is on technical questions of knowledge modelling and implementation. The genesis of the art historical conceptualization by experts on the subject of the Dutch Golden Age, which was guided by knowledge modelling expertise, will be presented elsewhere. Similarly, the use context of the presented ontology and knowledge base for data analysis, aggregation and visualisation related to the exhibition project is presented elsewhere [Sc17], [Is18].

## 2 Related work

Creation of a knowledge model in the digital humanities is typically used to provide a basis for exploring information and aiding in serendipitous discovery. An example of a project that aims for this is the ECARTICO database, which facilitates analysis of cultural actors and their social environments [Ni13]. Not yet available as Linked Open Data, it offers support for modelling social and genealogical networks of historical persons. In a similar vein, MapTap and the underlying database, Cornelia, model historical social networks of tapestry designers and entrepeneurs in 17th century Antwerp, Brussels and Oudenarde [Br16]. These projects build on the knowledge of art historians and archival sources. Our project builds on art historical literature and original work done in the context of the aforementioned exhibition project. In contrast to ECARTICO or MapTap which focus on social networks of persons, the core of our data model is concernend with relationships between works of art.

An important consideration when creating a data model is whether existing resources can be reused, for instance as top-level ontologies which guide the development of a model. The Europeana Data Model (EDM) [Do10] is a project that aims to provide a top-level ontology to facilitate exchange of information between different ontologies in the cultural heritage domain; the CIDOC CRM [Do03], which we used as a top-level reference model, assures that models based on it are compatible with a range of other specialized ontologies in the digital humanities and can be integrated into the EDM framework as well. To this end the EDM definition declares equivalences to CRM in its class and property descriptions where applicable [Eu16], and with a mapping of EDM to CRM proposed by the CIDOC CRM Special Interest Group [He15] this compatibility is further elaborated upon. Below the level of generality and abstraction typically exhibited by top-level ontologies, domain and application ontologies should reflect expert conceptualisations in a given domain and in addition facilitate search and retrieval of needed information by the intended audience. In the context of cultural heritage resources Pattuelli shows that taking a user-centered approach when designing an ontology, creating a prototype ontology based on user interviews and reworking the model with user feedback in mind, can yield a result that meets user needs more adequately [Pa11].

Modelling creative influence as weighted links between works of art leads to a networked representation akin to a social network graph. There is an abundance of literature on determining “influence” in networks and discovering interesting structures in edge-weighted graphs. Romero et al. [Ro11] present an algorithm to determine the influence of Twitter users. They are examining what qualifies for influence and how to quantify it in order to make predictions about behaviour; the art historians in the context of our project had to make decisions about what to qualify as an influence and quantify its effect, albeit not with algorithms but by studying the artworks and using observations and hypotheses documented in relevant literature to determine the likelihood of influences. The degree of influence of a piece of art can be seen as analogous to what Romero et al. describe in their work: as Twitter users' influence may be, among other aspects, approximated by the amount of retweets of their content [Ro11], the influence of an historic piece of art may be estimated by the number and nature of subsequently influenced works. Modelling a data structure to allow algorithmic analysis as Romero et al. have done in their work may allow for further art historic insights. The Oddball algorithm [Ak10] aims to find anomalies in weighted graphs. Assuming the data gathered by art historians can be abstracted to a weighted graph of influences, an algorithm such as this may lead to new discoveries or confirm assumptions about the data. Modelling an ontology that adequately describes influence properties may for example show "cliques"[Ak10] of highly interconnected neighbourhoods of artworks or "stars" [Ak10] or near stars, i.e. works that inspired a number of disconnected neighbourhoods, such as works which were received or responded to in various different ways. Examining such structures may provide new insights into possible interactions between artists that were not previously suspected or described in historic documents and may then be further analysed in order to determine their validity.

## 3 Modelling decisions

In a similar vein to Pattuelli [Pa11], albeit on a smaller scale and more informally, we continuously incorporated results from discussions with art historians that helped clarify the nature of the data and how it could best be represented into the design and implementation of our data model as part of an iterative development process.

The starting point for our discussion here, which focuses on the more technical questions of knowledge modelling and implementation, is the semi-formal conceptualization of how inspiration taking can manifest itself in two works of art. This conceptualization was agreed upon by art historians and arrived at after discussions with knowledge engineers.[3] According to this conceptualization, an artwork shows influence by another work of art (Fig. 1) or two works of art document an influence the source of which cannot be determined with any certainty (i.e. it is unclear which of the two works was the influencer, Fig. 2).

Judgements of this kind are subject to qualitative criteria that describe the "connection strength", which expresses the degree of similarity between the paintings, and likelihood of the influences in five discrete categories each. The concept of "connection strength" is intended to express the degree to which one work was inspired by an other, ranging from

[3] The second author has been involved in discussions on how to formalize certain relevant art historical intuitions for the exhibition project mentioned above from an early stage of planning on. This process will be documented separately.

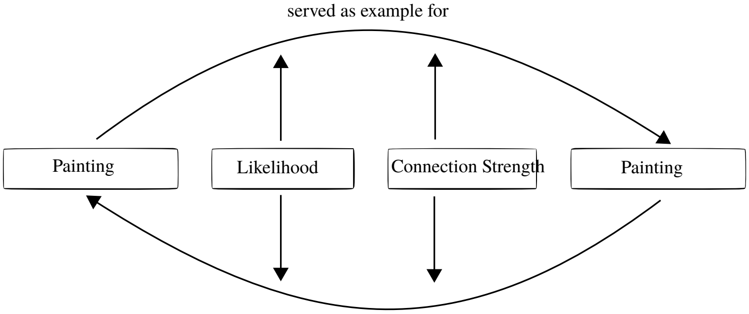


Fig. 1: Informal concept of a model for directed influences: an influence is characterized by a painting that served as an example and a painting that was inspired by it. The influence is further qualified by measures for “likelihood” and “connection strength” of the proposed connection.

paintings that only vaguely reflect another work through a number of indistinct elements (connection strength 1) to works that can be classified as a copy, partial copy or pastiche of another work (connection strength 5). These categories for both connection strength and likelihood were chosen as part of a deliberation process between art historians and knowledge engineers. The likelihood categories (“certainly”, “most likely”, “probably”, “possibly” and “perhaps”) were inspired by terminology commonly used in art historic literature to qualify statements in terms of their likelihood or probability.

Additionally, both qualitative descriptions received numeric values for each of their categories, to facilitate data aggregation and analysis. Both, the number of categories and the respective numeric values assigned to these for aggregation purposes, are not to be interpreted as final and unchangeable settings, but rather as one possible approach to qualify these influences. Modelling probabilities as discrete values instead of a continuous range of values was suggested by the data gathering process: art historians compiling and gathering influence probabilities may assign granular distinctions of probabilities to different influences; using continuous probability values can lead to disagreements between experts, as historic sources cannot be regarded as positive proof for these probabilities and

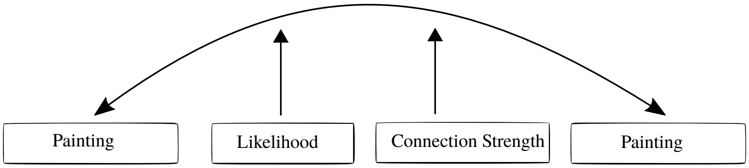


Fig. 2: Informal concept of a model for undirected influences: analoguosly to the directional concept, the influence is qualified by measures for “likelihood” and “connection strength”. The direction of influence, however, is not specified.

are themselves open to interpretation by experts. Using fewer and discrete probabilities may allow for a more agreed upon vocabulary and a more consistent use.

The informal conceptualization illustrated in Fig. 1 and 2 implicitly assumes an historic causality behind the influences documented. Each conjectured influence is thought to have arisen from an historical constellation in which one artist got to know about another work either through first hand experience, through sketches or prints or otherwise and consequently adopted certain elements into one of his own creations.

The complexity that art historians associated with the inspirational connections between works called for a semantically rich modelling that goes beyond a simple relational link. We followed an event-based approach for this as it allows great flexibility in what additional information can be attached to the links. On the basis of the informal conceptualisation and discussions with art historians, a first intuition was to interpret the over 900 instances of individual connections between works of art present in the data as historical events of the Dutch Golden Age and possible semantic models were evaluated. The chosen model should support the modelling of art historical concepts should facilitate integration with other models, to allow interconnection with related data sets in the digital humanities. The Simple Event Model (SEM) [Va11] tries to describe a generalized event model with domain agnostic vocabulary and meets our needs, but provides only very generic vocabulary.

A candidate for an extensive formal top-level model in the digital humanities domain is the CIDOC Conceptual Reference Model (CRM) [Do03]. CIDOC CRM was created specifically for the cultural heritage domain, with definitions and formalizations that help map heterogeneous data from different contexts to a common model. This proved helpful in our case, as for example creator-artwork connections were already implicitly modeled and could be readily used. Translating the entities, object and data properties to a semantically rich description language such as OWL allows for expressing cardinality constraints and other axiomatizations. CRM concepts as defined in the official description of the standard [Le15] can be mapped to OWL and RDF constructs. This was done by Goerz et al. in the form of the Erlangen CRM [Go08], which is an OWL implementation of the CIDOC CRM. Using an OWL implementation instead of the official RDF representation of CIDOC CRM [Fo15] also granted more axiomatic expressiveness. In contrast to CRM, generalized models like the SEM do not provide built-in concepts close to the art historical domain, such as material works and their creation process, and were ultimately not considered.

In further discussions with art historians, the previous assumption of influence between works of art as art historical events for the purposes of the model was replaced with a more abstract proposition: the individual influences gathered in the data, characterized by qualitative criteria, can alternatively be modelled as appraisals by art historians. Modelling the influences in this way instead of as distant historical events represented the actual data compiled by the art historians much more accurately. This also avoided difficulties regarding the estimation of likelihood, which otherwise would have to be interpreted as expessing a strong claim about the probability with which a not very precisely defined historic event

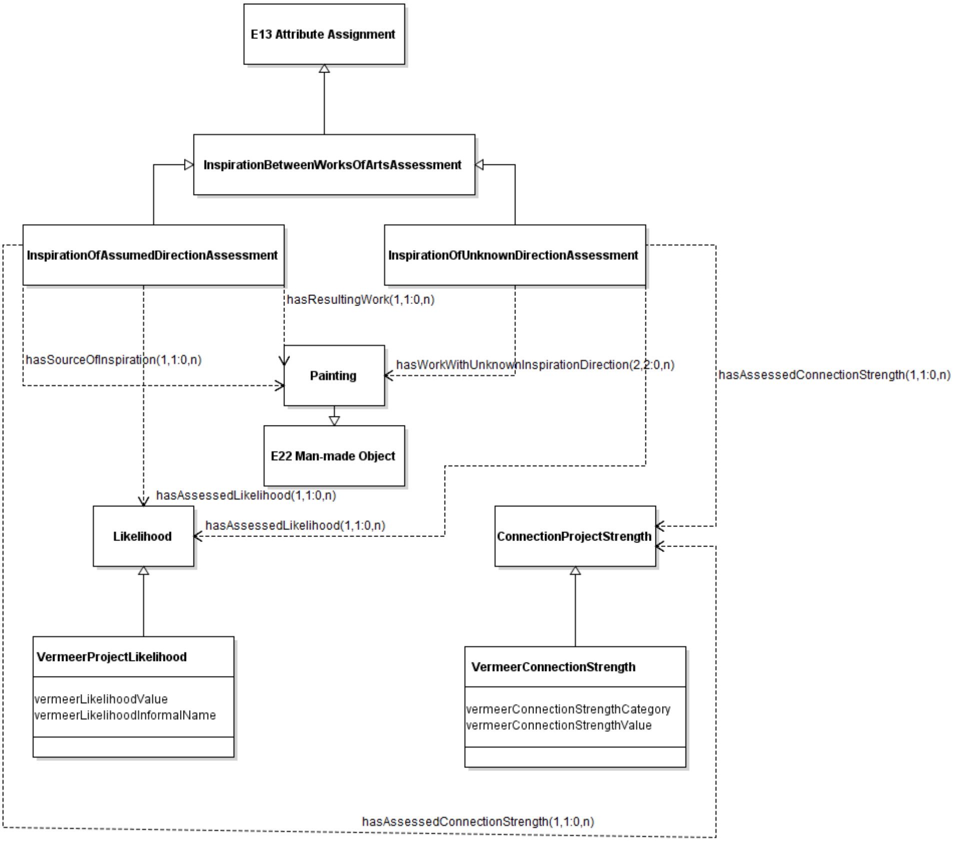


Fig. 3: Influence Assessment: this overview of the core model shows assessment classes and their connections to "Painting", "Likelihood" and "ConnectionStrength" classes, including cardinalities; dotted arrows represent object properties with cardinalities, solid arrows mark subclass relationships.

(roughly one artist taking inspiration from someone else's work) occurred centuries ago. Focusing on expert appraisals instead, the likelihood refers to the appraisal itself, i.e. the certainty or uncertainy an art historic scholar assigns to his or her judgement. This is closer to our data and led to the CRM "E13 Attribute Assignment"[4] class [Le15] as the core class of our model extension (cf. Fig. 3). This is sub-classed with two different assessment entities, that describe creative influences of assumed direction (work A served as example for work B) and creative influences between artworks with unknown direction (work A and B influenced each other, but it is unclear which one served as example), corresponding to the informal conceptualisations presented in Fig. 1 and 2, respectively.

[4] CRM denotes classes with a capital E (for entity) followed by a number.

To model likelihoods and connection strengths, “Likelihood” and “ConnectionStrength” OWL-classes were created; these were sub-classed with the specialized “VermeerProjectLikelihood” and “VermeerProjectConnectionStrength”. The CRM provides most concepts needed to readily organise the data in CRM form: artists are modelled as instances of the CRM “E39 Actor” class, the production of works of art, needed to connect artists and the artwork, is represented as a CRM “E12 Production” instance. The extension of CRM “E13 Attribute Assignment” with a “VermeerProject_InspirationBetweenWorksOfArtAssessment” sub-class, which in turn is subclassed by “VermeerProject_InspirationOfAssumedDirectionAssessment” and “VermeerProject_InspirationOfUnknownDirectionAssessment”, models the needed concepts of known and unknown influence directions. CRM “E22 Man-Made Object” is extended with a “Painting” class for the works of art. The CRM properties “P108 has produced”, with its inverse “was produced by”, and “P14 carried out by”, with its inverse “performed”, are used to connect the “Painting” class with “E12 Production” and ”E12 Production” with “E39 Actor”, respectively. Self-defined properties outside of the CRM scope include “hasVermeerProjectSourceOfInspiration” and “hasVermeerProjectResultingInspiredWork” to connect “Painting” instances to “VermeerProject_InspirationOfAssumedDirectionAssessment” instances. Similarly, “hasVermeerProjectWorkWithUnknownInspirationDirection” connects instances of “Painting” to instances of “VermeerProject_InspirationOfUnknownDirectionAssessment”. To define the assessments’ likelihood and connection strengths, “hasVermeerProjectAssessedInspirationConnectionStrength” and ““hasVermeerProjectAssessedInspirationLikelihood” describe instances of “VermeerProject_InspirationBetweenWorksOfArtAssessment” and its sub-classes. To make queries easier, two shortcut properties were also created: “isProducerOfThing” and its inverse “isProductOfActor”, which shortcut “Painting” - “E12 Production” - “E39 Actor” relationships in both directions. Further properties include “hasEarlyDate”, “hasLateDate”, “hasTitleEng”, “hasTitleNld” and “rkdWorkOfArtNumber”. These are used to further describe “Paintings”. The “vermeerConnectionStrengthCategory”, “vermeerConnectionStrengthValue”, “vermeerLikelihoodInformalName” and “vermeerLikelihoodValue” properties are used to describe the “VermeerProjectLikelihood” and “VermeerProjectConnectionStrength” classes. Finally, “vermeerProjectCredits” and “vermeerProjectDescriptionOfAdoptedElements” connects further descriptive data to the “VermeerProject_InspirationBetweenWorksOfArtAssessment” class instances. Fig. 3 shows the core model of inspiration/influence assessments.

The influence assessments collected by the art historians include assumptions about their likelihood and connection strength. We opted to create generic Likelihood and ConnectionStrength entities to represent these in the model, which were sub-classed with our specialized likelihood and connection strengths that were created for the influence assessments. This approach was taken to allow for different conceptualizations of uncertainties and connection strengths in other use cases, such as future projects in other art domains for instance. The final implemented project specific entities for Likelihood and ConnectionStrength were moved to a separate small application ontology which contained Vermeer project specific likelihood and connection strength terminology and values as enumerated classes VermeerProjectLikelihood and VermeerProjectConnectionStrength (cf. Fig. 3). Enumeration was chosen, as the Vermeer project likelihood and connection strengths were each manifested in five categories, "certainly", "most likely", "probably", "possibly" and "perhaps" for likelihoods and ascending numbers from one to five for connection strengths, each of which had assigned numeric values for exploratory and analytical purposes. The categories and values for likelihoods and connection strengths were encoded as data properties for the instances of the likelihood and connection strength classes. This small ontology can readily be exchanged for other likelihood and connection strength scales if needed. The influence assessments, represented by "VermeerProject_InspirationBetweenWorksOfArtAssessment" and its sub-classes "VermeerProject_InspirationOfAssumedDirectionAssessment" and "VermeerProject_InspirationOfUnknownDirectionAssessment", were qualified by a source for the assessment attached as a literal string data property "vermeerProjectCredits", which took the form of a bibliographic reference, if the assessment was gathered from the literature, or the name of an art historian associated with the exhibition project, if the assessment was made as part of the project. The influence assessments were further described by the string valued data property "vermeerProjectDescriptionOfAdoptedElements", to inform about elements that prompted the influence assessment.

As we were looking to include Linked Open Data sources to augment the available data, there were two obvious areas we tried to import external controlled vocabularies for, if feasible: the artists and the paintings occurring in our data set. Getty ULAN (The Union List of Artist Names) [Ab15b] provides comprehensive data about alternative names and spellings, relationships, roles and other information. It is a "vocabulary containing names and other information about artists, patrons, firms, museums, and others related to the production and collection of art and architecture." [Ab15b]. Getty ULAN provides valuable augmentation to our data, as the raw data itself only contained artist names and no further information. The ULAN artist vocabulary is imported for use into our ontology. The production of paintings is modelled as a CRM "E12 Production" entity, which, among other properties, includes inherent properties that could model our data, such as the "P14i performed"[5] and its inverse "P14 carried out by" object properties [Le15]. The defined domains and ranges of object properties allow reasoners to infer used Getty Vocabulary Program ontology (GVP) class instances to belong to a CRM class (e.g. GVP Subject or PersonConcept instances can be inferred to be in the "E39 Actor" CRM class). This allows for a semantic connection between the artist and his painting via a CRM "E12 Production" entity. We furthermore defined axiomatic shortcut-properties on the basis of the CRM properties, to facilitate easier queries. One such shortcut, "isProductofActor" directly connects a painting and its creator (cf. Fig. 4).

We also looked at possible sources for the augmentation of artwork data. There are databases available, like Getty CONA (Cultural Objects Name Authority)[Ab15a], that

[5] "performed" is defined as the inverse property to "P14 carried out by" property in CRM; the "P14i" notation is an Erlangen CRM convention to signify the inverse nature of the property

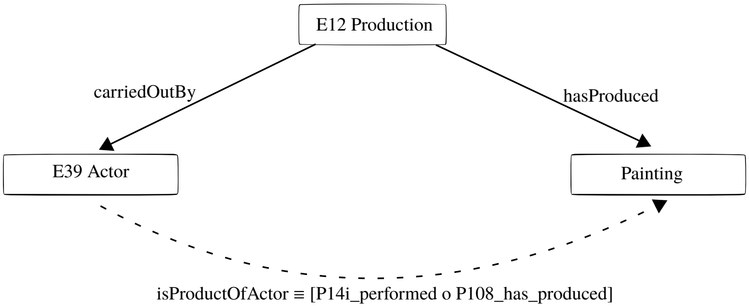


Fig. 4: The Painting and E39 Actor classes are connected by a E12 Production class. The shortcut "isProductOfActor" is defined as a concatenation of the "P14i performed" and "P108 has produced" object properties.

collect information about cultural artifacts or works of art, but unlike Getty ULAN they are not available as Linked Open Data and could not be imported like Getty ULAN. Instead we allowed the instances of the "Painting" class to have several data properties to include more information about the works of art: As our data included RKD artwork numbers[6] for the paintings, we carried those as a data property "rkdWorkOfArtNumber" for future reference. Artwork names are encoded as "hasTitleEng" and/or "hasTitleNld" data properties, if the data declares an English and/or a Dutch name. "hasEarlyDate", "hasLateDate" data properties take the two dates present in the data for each work of art, which represent the earliest and latest date of the likely completion of a painting.

These dates and their meaning were also a point of consideration: Our data contained time spans, which were represented by a pair of years, that marked the assumed earliest and latest date of the time spans. Studying the CRM specifications, the CRM already accounted for inaccurate or imprecise time spans through its "P81 ongoing throughout" and "P82 at some time within" properties, that describe the minimum and maximum period of a time span respectively [Le15]. A proposed way to map these properties to RDF (and by extension to OWL) was outlined in a document on the CIDOC website [Ho11]. We ultimately decided to not pursue the date modelling further at this stage, as the art historians did not assign a high priority to this aspect (apart from displaying dates or date ranges as part of the "tombstone information", i.e. the little record typically displayed together with an image of the work). A more detailed and sound modelling of the time spans may be part of future work.

Summing up the choices outlined above, we used Erlangen CRM as our CIDOC CRM implementation, Getty ULAN as a controlled vocabulary for integration of artist information, our own auxiliary ontology for likelihoods and connection strengths and project specific entities and properties that we created on the basis of available Vermeer project data.

[6] RKD art work numbers are record numbers assigned by the RKD-Nederlands Instituut voor Kunstgeschiedenis (Netherlands Institute for Art History) to works of art in their collection.

# 4 Conclusion

We have outlined our approach to modelling the semantics of data describing influences and inspirations between works of art, based on OWL/RDF and the CIDOC CRM [Do03], [Le15]. Choosing the CRM allowed us to focus on the core of our model (the influence description) and take advantage of preexisting properties and entities. Using the CRM, specifically the Erlangen CRM OWL implementation, ensured basic compatibility with other ontologies that use CRM specifications while at the same time providing the flexibility of defining specialized entities for our purpose. Because of the generalized nature of the CRM, importing the Getty ULAN [Ab15b] controlled vocabulary to provide further information about artists in the data set did not present a problem and integrated seamlessly. Importing our own auxiliary ontology for likelihood and connection strength measures was similarly straightforward. The artworks should ideally also be linked to an external source of information. As described above, we have not yet done this, as a source as readily usable as ULAN is for artists is not available for works of art and modelling this in detail was not a priority at this stage. We hope that Getty will make their CONA [Ab15a] database available as Linked Open Data in the future. The modelling of dates, although an important aspect in art historical contexts and also relevant for questions of causal influence between two works, was so far only done in a rudimentary form; presently all dates are attached as literals to the painting instances in the knowledge base. Further considerations in connection with the use of more precise sources should lead to a more precise modelling of dates present in the data.

Possible use cases of the described conceptual model and the data organised accordingly are discussed in a separate publications [Sc17], [Is18]. [Sc17] presents a visualization framework which builds on the knowledge model and data described here. The framework facilitates browsing and exploratory analysis. [Is18] explores the artistic influences between cities in the Dutch Golden Age by aggregating influences taking into account the likelihoods and connection strengths, in different ways; comparing different aggregation methods to each other and to expert rankings may confirm the "gut-feeling" of experts with regard to the importance of certain cities and/or show unexpected insights, that could warrant further art historical research. Modelling an ontology for this domain and collecting data according to it may thus support and perhaps intensify the analysis and discovery of art historic facts and connections. New art historic insights may also be possible, by employing graph and network analysis along the lines of [Ak10] and [Ro11] which we intend to explore once the more straightforward aggregations and visualisations have been evaluated.

We have presented an ontology to model the influences between works of art, specifically genre paintings of the Dutch Golden Age. Invariably some of the choices and conceptualisations made will have been influenced by the particularities found in the paintings of the 17 masters included in the exhibition and the ways they looked at and responded to each others works. Nevertheless we hope that the model presented here, which was designed and implemented with generality and modularity in mind, will be robust enough to inform the formalized description of hitherto unrecorded creative influences either as an organic expansion of the current dataset or by transferring the model or parts of it to such influences as may be observed in creative endeavours of different eras and of different natures.

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