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I. Introduction

The communion of saints presents a view of the Christian community that spans space, time, life, and death. Medieval iconography captures and preserves the evolution of the communion by documenting the integration of new saints with the established imagery of saints in the communion. In the development of the iconography of Saint Francis (1182 - 1226) in the Thirteenth and Fourteenth Centuries, artists and their patrons exerted great effort to associate St. Francis with this rich tradition of imagery. In fact, the associations of saints in medieval paintings provide a basis for studying the development of iconography as a network of saints who appear together in an image. In other words, networks and data mining techniques can provide insight into the communion of saints as well as the iconographic tradition that visualized the communion in the Middle Ages.

Researchers have already used co-occurrence networks to study iconography (Birnbaum et al; Lombardi, 2013; Lombardi, 2014) and the breadth of subjects addressed with such networks is breathtaking (Veling & van der Weerd, 1999; Alberich et al., 2002; Saito et al., 2007; Rabbat et. al., 2008; Araύjo et al., 2011; DeScioli et al., 2011). Suffice it to say that scholars have developed many techniques for constructing and analyzing networks of people from digital images (Golder, 2008; Kim et al., 2010; Kim et al., 2012) and that these techniques can be applied to the images of saints in medieval paintings. The resulting co-occurrence networks have structural properties similar to those of other networks including hubs (nodes of high degree), high clustering coefficients and short average path lengths between nodes. Furthermore, these networks provide compelling examples of preferential attachment, whereby the network evolves by attaching new nodes, in this context recently canonized saints, to those nodes with high degree such as Christ and Mary. In a sense, therefore, the network structure captures the intercessory function of these images by showing the frequent juxtaposition of lesser known saints with those of enduring prestige.

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The current study extends these approaches by modeling the interaction of saints as directed networks. After outlining the theological, artistic, economic and technical background motivating this research, the paper outlines a technique for inferring the relative prestige of medieval saints in a corpus of artwork. Using a corpus of early images of Saint Francis of Italian production (Cook, 1999), the paper demonstrates how to use the confidence metric commonly found in association rule mining to construct a directed network. Directed networks provide many ways to estimate structural prestige (popularity) in a network. By studying the directed structure of these networks over time, art historians will have a set of powerful tools with which to analyze the traditions of medieval iconography.

After providing the details of the technique, the study verifies the technique for effectiveness with some baseline tests. First, we expect the popularity of Christ and Mary to be consistently high across the corpus given the important theological role their images played in the artwork. Second, the prestige figures should register important historical events such as the canonization of saints. The study also employs the prestige measurements to test art-historical claims related to this corpus. In particular, the study evaluates the claim that non-Franciscan houses chose to portray Francis differently from the compositions chosen by other patrons. Finally, we assess the popularity metrics as a tool for exploratory analysis to gauge their utility in discovering interesting trends for further research.

In concluding remarks, the paper reflects on the role these techniques might play in more ambitious art-historical research projects. The conclusion assesses the prospects of applying distant reading to visual culture. We explain some current shortcomings that challenge this vision including several kinds of bias researchers encounter in this kind of data. Despite such shortcomings, we believe that these techniques may shed light on one of the most persistent problems in the interpretation of fourteenth-century Italian art: the influence of the Black Death. Finally, the paper summarizes some promising directions for future research in this topic.

II. Background and Previous Work

In many ways network analysis and data mining approaches to the content of artwork are unconventional choices requiring justification. The approach taken in this paper relies on three motivating ideas. First, medieval theology, specifically the concept of intercession, suggests a process for the formation of networks of saints. Second, art historians widely recognize the intercessory function of much medieval artwork and have begun recently to interpret these functions in networking terms. Third, the complex interactions between patrons and artists, as defined by contract, drove the market for intercessory images in the Middle Ages. Network analysis and data mining provide particularly useful ways to capture the iconographic trends resulting from these theological, artistic and economic forces.

The medieval notion of intercession implies a kind of network process linking Christ to saints and saints to the faithful. The epistles of the New Testament outlined the biblical origins of this idea clearly: "For there is one God, and also one mediator between God and men, Christ Jesus" (I Timothy 2:5-6). Over the course of the Middle Ages, this idea grew into an elaborate architecture of ideas and images. Brian Patrick McGuire traces this development, its formal description as the communion of saints, and its connection to the growing importance of purgatory. McGuire summarizes the medieval notion of the communion of saints in terms of "reciprocal contacts" among the faithful on earth, the suffering in purgatory and the saved in heaven (p. 67). Artistic production in the Thirteenth and Fourteenth Centuries captured these reciprocal contacts in the intercessory images produced for individual and institutional patrons.

Art historians have long recognized the intercessory function of medieval religious art and recently have started to express these functions with network terminology. In his recent analysis of deësis composition and intercessory imagery, Sean Gilsdorf has applied the formal terms of social anthropology to the interpretation of medieval artwork. Specifically, he argues that intercession constitutes, borrowing the language of anthropologist Philip Gulliver, "triadic interactions" (p. 133). This insight demonstrates a strong convergence with the terms and tools of network analysis including important processes driving link formation in social networks such as triadic closure (Easley & Kleinberg, p. 44) and typical ways of describing the results of these processes like triadic census (DeNooy et al., pp. 234-243). Gilsdorf's study highlights the deësis group as one such important triad, "in which Christ was depicted flanked by the Virgin Mary on one side and John the Baptist on the other" (p. 134). Network analysis provides a well-understood set of tools for evaluating such artistic motifs in medieval art.

The tastes, interests and wealth of patrons in Italy in the Thirteenth and Fourteenth Centuries drove the demand for intercessory images including those in the corpus used in this study. In her study of painting in Siena after the Black Death, Judith Steinhoff refers to art patronage during this period as "a vital instrument of cultural expression" (p. 29). Governments, religious institutions, and individuals contributed to the development of iconographic images by expressing and defining their tastes via contracts for specific works of art. In this market for imagery, some iconographic trends became more or less popular as individuals and groups responded to the complex interactions of popular devotion, theology, artistic skill and regional preferences. These differences over time resulted in changes in the selection and preference for saints in artwork. Data mining techniques provide a basis for analyzing the selection of saints in specific works that supports and augments the network analysis of these market-driven iconographic trends.

Scholars have already started to explore medieval visual and devotional culture with network models. For example, a group of researchers have recently used a social network analysis of Orthodox saints in medieval manuscripts "as a tool for clustering manuscripts and formulating hypotheses about textual transmission and diffusion" (Birnbaum et al., 2013). Network analysis has also been applied to the study of Franciscan iconography specifically (Lombardi, 2014). In the latter study, two saints were considered to be connected if they were depicted together in an image. Moreover, each additional image including both saints increased the weight of the link between those saints. In treating the co-occurrence of saints like a social network derived from images (Golder, 2008), researchers have been able to identify some interesting structural properties of such networks. Figure 1 presents the entire network derived from the co-occurrence of saints in a corpus of early images of St. Francis. Popular saints, known by their high degree, such as St. Francis, St. Clare and St. Anthony of Padua appear just below Christ and Mary.

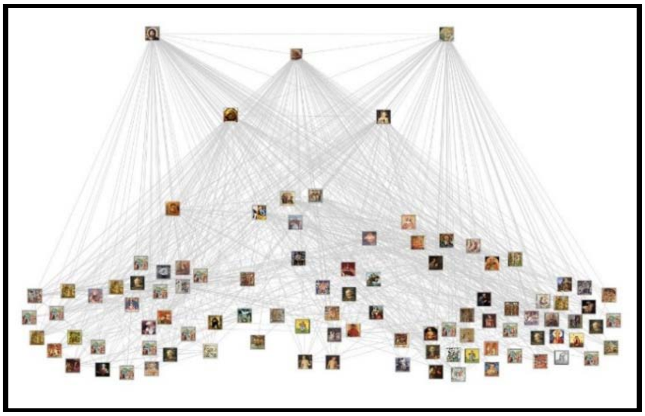

Figure 1 : Co-occurrence network of saints

Unfortunately, these kinds of networks do not easily capture the known ranks in such iconography. For example, the presence of St. Anthony of Padua, a Franciscan saint, depends on the presence of St. Francis in two ways. Historically, St. Francis was the head of the Franciscan order and therefore Anthony depended on the institution named for Francis. Artistically, St. Anthony does not appear without Francis in imagery at this time (Cook, pp. 262-263). In order to capture the development of this imagery in more detail including the hierarchical aspects of the organization of these saints, the technique must capture the direction of links to represent these dependencies. The Data and Methods section of this paper outlines an approach for constructing a directed network from co-occurrences.

Directed links offer interpretive advantages over the undirected links in previous studies for several reasons. First, directed links capture the hierarchical relationships in the iconography more naturally. For example, a directed link from St. Anthony of Padua to St. Francis captures the historical and iconographic dependence between the two saints. Second, directed links provide several techniques for calculating structural prestige. In other words, by adding direction to the links connecting saints we can estimate a saint's relative popularity (prestige) in a number of ways. In order to achieve this, however, the undirected co-occurrence network must be converted to a directed network.

Association rule mining from data discovery research is one such technique for accomplishing this. Association rules were originally developed to process sales transactions by performing market basket analysis (Kotsiantis & Kanellopoulos, 2006; Agrawal et al., 1993; Chen et al., 1996). In such studies, researchers glean the purchasing habits of shoppers by identifying items commonly purchased together. Given that medieval patrons and artists chose compositions with specific arrangements of saints and symbols, this study treats each work of art as a basket filled with iconographic images. This technique provides several metrics for determining the strength and direction of these associations. In particular, the confidence measurement, explained in detail below, establishes a basis for inferring directed relationships between saints. In other words, by identifying the saints commonly presented (purchased) together, researchers can model the relative prestige of saints over time to understand better the economic, artistic and theological processes driving the development of these images.

By combining association rule discovery and network analysis researchers can capture the relationships between saints in images in greater detail. Directed links offer some additional analytical power pertinent to the analysis of iconographic trends. First, directed networks allow for the calculation of prestige. Given the nature of medieval iconography, inferring the prestige of saints can help to compare regional and temporal trends. Second, directed links, and the prestige measurements they make possible, provide a useful framework for testing art-historical hypotheses and even performing exploratory analysis. Therefore, the combination of these techniques offers us insights into the complex interactions of theology, art and economics that influenced the production of these works.

III. Data and Methods

The corpus, compiled by Cook, includes 236 images of Saint Francis of Italian production from 1230 to 1330 (1999). Cook's catalogue serves as an excellent starting point for this study because it solves many technical and practical problems. The catalogue provides information about dating, provenance, authenticity, style and documentation. More importantly, the iconography of Francis provides a dramatic example of a transition from regionally-venerated to internationally -venerated saint. The techniques outlined in this section along with previously developed networks (bipartite, time-event) provide powerful ways to model and analyze these iconographic transitions and trends.

The technical process of building the directed network involves standard techniques in data mining and network analysis. Cook's corpus was converted into a matrix for association rule mining in RapidMiner. The data were denormalized to capture the presence or absence of a saint in each painting. The resulting matrix includes 236 rows representing the paintings and 102 columns representing the saints. After preparing the data, support and confidence metrics for each pair of saints were calculated. The rules produced directed weighted networks which were exported and analyzed in Pajek. The confidence metrics capture the strength of the relationship between saints in each direction, providing a basis for inferring rank in the relationships (Figure 2). For example, the thick pink link from Anthony to Francis is represented with a confidence of 1.0, meaning that every time Anthony appears in an image we can be certain that Francis will appear as well. The thin blue link from Francis to Anthony on the other hand

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has a confidence of 0.122, signifying that Francis appears without Anthony in many paintings. Cytoscape was used to produce network visualizations like those in Figures 1 and 2.

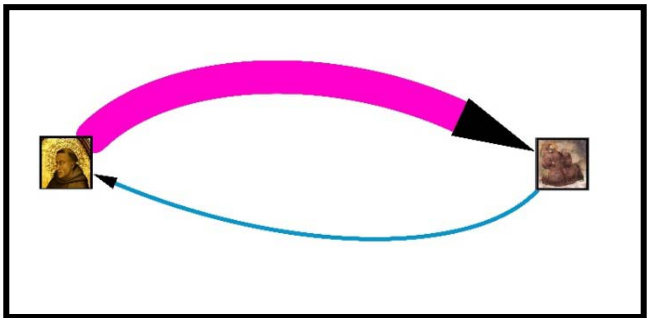

Figure 2 : Directed links between Anthony of Padua (left) and Francis

For the purposes of demonstrating the proposed technique, we will outline the technique with three of the earliest images in the catalogue including the *Pescia Dossal* (Figure 3). The painting includes three recognizable figures: St. Francis, the Seraph, and Bartholomew of Narni. Each painting, listed by its catalogue number, constitutes a row of data. The columns record a saint's presence in the painting with a 1 and a saint's absence in the painting with a 0. For instance, the first row of Table 1 captures the co-occurrence of Francis, the Seraph and Bartholomew of Narni in the *Pescia Dossal* (Cook, p. 141). For the purposes of this demonstration, Table 1 also includes the data associated with two other early paintings from the Cook catalogue.

Table 1 : Denormalized Painting Data

Cook #	Narni	Seraph	Francis	Gregory IX
141	1	1	1	0
193	0	0	1	1
10	0	0	1	0

After compiling the data in denormalized format, support and confidence metrics provide a basis for constructing a directed network. For each saint individually, the support is the number of times a saint appears in an image divided by the total number of images which in this case is three (Table 2). For each pair of saints, the support is calculated by counting the number of times the two saints appear together in an image divided by the total number of images in the data set. For example, Seraph and Francis appear together in 1 of 3 images yielding a support of .3333. RapidMiner uses the FP-Growth algorithm for generating support metrics (Han et al., 2000).

Table 2 : Support Calculations

Saint	Appearances	Support
Francis	3	3/3 (1.0)
Seraph	1	1/3 (0.33)
Narni	1	1/3 (0.33)
Gregory IX	1	1/3 (0.33)
Francis,Seraph	1	1/3 (0.33)
Seraph,Narni	1	1/3 (0.33)
Francis,Narni	1	1/3 (0.33)

Figure 3 : Bonaventura Berlinghieri, Pescia Dossal, 1235 (Cook 141). Photo Credit: W. R. Cook.

The support metrics serve as the basis for computing the confidence of each directed link between saints. Table 3 summarizes these calculations for the sample data. Unlike the support metrics which have no inherent direction, confidence metrics are directed because the confidence of A→B is not necessarily the same as the confidence of B→A. For example, the confidence of Francis→Seraph is 0.3333 whereas the confidence of Seraph→Francis is 1.0. In other words, in this set of sample data, every time a painting includes a Seraph it also includes Francis. On the other hand, observing Francis in this data set does not guarantee that the Seraph will also be in the image. The absolute value of the difference between the confidence of the arcs between Francis and Seraph determines the weight and direction of the link between the two nodes in the network.

Table 3 : Confidence Calculations

Antecedent→Consequent	Confidence
Francis→Seraph	0.33/1.0 = 0.33
Seraph→Francis	0.33/0.33 = 1.0
Francis→Gregory IX	0.33/1.0 = 0.33
Gregory IX → Francis	0.33/0.33 = 1.0
Francis → Narni	0.33/1.0 = 0.33
Narni → Francis	0.33/0.33 = 1.0
Seraph → Narni	0.33/0.33 = 1.0
Narni → Seraph	0.33/0.33 = 1.0

Table 4 demonstrates the final calculations required to construct the network. In the case where the link weights are not equal, the link direction is that with the highest confidence. In the case of the Seraph and Francis, the Seraph→Francis link is preserved. The weight of the link is the absolute value of the difference between the links. In cases where the link weights are equal, the link is a bi-directed link with the confidence serving as the weight. For example, the Seraph and Bartholomew of Narni have the same confidence in both directions therefore this relationship is represented as a bi-directed link with a weight of 1.0.

Table 4 : Link Weight Calculations

Link	(A→B)	(B→A)	Weight
Seraph→Francis	1.0	0.3333	0.6667
Gregory IX→Francis	1.0	0.3333	0.6667
Narni→Francis	1.0	0.3333	0.6667
Seraph←→Narni	1.0	1.0	1.0

When these directed and bi-directed links are combined (Figure 4), they produce a directed weighted network well-suited to determining popularity. Directed networks provide several straight-forward and intuitive techniques for estimating prestige (DeNooy et al., 2011, pp. 215-228). The input degree is the number of links pointing to a particular node in a directed network. In the sample network, Francis has an input degree of 3 while Gregory IX has an input degree of 0. Although input degree is often illuminating, this measure of prestige only addresses direct connections. The influence domain is the proportion of all other nodes connected by a path to a particular node. Three saints can reach Francis while Seraph and Bartholomew of Narni can only be reached by one other saint. The input proximity prestige divides the influence domain of a particular vertex by the average distance from every node in the influence domain. Table 5 summarizes the calculations required to compute the input proximity prestige in a directed network. Each of these measurements highlight Francis as the most prestigious saint in this simple network.

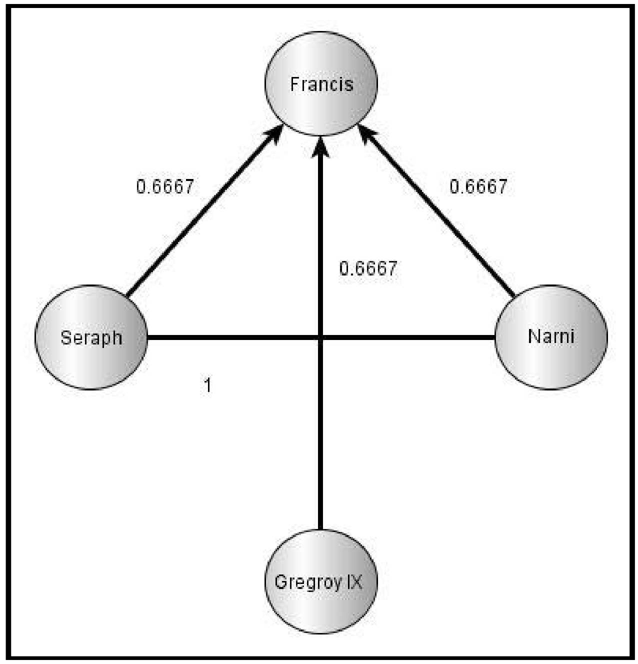

Figure 4 : Directed, Weighted Network of Saints

Table 5 : Input Proximity Prestige Calculations

Saint	Influence Domain	Prop. Distance	Avg. Dist.	Prestige
Francis	3	1.00	1.00	1.00
Seraph	1	0.33	1.00	0.33
Narni	1	0.33	1.00	0.33
Gregory IX	0	0.00	Undefined	0.00

The process outlined above was performed for each saint in each decade of the corpus. The raw results of this analysis are available in spreadsheet format from the author. The data mark saints who do not appear in any artwork during a particular period with a value of -0.1 to distinguish them from those saints who appear in the artwork of the time with prestige values of 0. This data supports several kinds of analysis performed in the next section including correlation of prestige figures, hypothesis testing and exploratory analysis.

IV. Results and Analysis

In order to evaluate the results, the technique had to be validated with some baseline tests. First, we expect the prestige of Christ and Mary to be consistently high across the corpus given the important theological role their images played in the artwork and the society that produced it. Somewhat surprisingly, the painters and patrons of the earliest surviving images of Francis from the 1230s and 1240s did not seek to juxtapose Francis with Christ, Mary or other globally-recognized saints. Instead, the early promoters of Franciscan iconography chose to portray Francis by himself or with other prominent figures in Francis's hagiography such as the Seraph. As the cult of Francis grew, however, the prestige of Christ and Mary jumped from nil in the 1240s to 0.97 and 0.79 respectively in the 1320s (Figure 5).

Second, the prestige measurements should register important historical events such as the canonization of the saints. As expected the prestige of St. Clare and St. Louis of Toulouse peaked during the periods of their canonization. For example, Louis of Toulouse was canonized in 1317 and his prestige in this period rose to 0.33 from nil in the previous decade. During the same time period, the prestige of Anthony of Padua, another male Franciscan saint, plummeted to 0.0 from 0.45 (Figure 6). As a popular new saint, Louis displaced Anthony for about a decade as the preferred male Franciscan to balance compositions with Francis. We found similar results for St. Clare, canonized in 1255. During the decade of her canonization, her popularity (0.53) outstripped even that of Anthony of Padua (0.47). She would not attain this level of prestige again until the 1300s.

Having performed some basic verification of the technique, we wanted to use the prestige metrics to test art-historical claims related to this corpus. For example, Cook argues that non-Franciscan houses, such as those of the Dominicans and Benedictines, adjusted their images of Francis to reflect more modest views of the saint's iconography (p. 103). In particular, non-Franciscan houses often portrayed Francis without the stigmata, the wounds of Christ. The prestige trends provide some support for this assertion. We observe a negative correlation between the prestige of the Seraph and both St. Benedict (-0.49) and St. Dominic (-0.58). In other words, as the prestige of Benedict and Dominic increased, the prestige of the Seraph, the agent of Francis's stigmata, decreased. On the other hand, a negative correlation was also found between the Seraph and prominent Franciscan saints: Clare (-0.79) and Anthony of Padua (-0.39). Therefore, the prestige metric may be identifying differences in the composition of these works in a fairly broad way. While the Seraph features prominently in the hagiographical traditions related to Francis and often appears in artwork focused on those traditions, patrons focusing on non-narrative intercessory images might have excluded the Seraph for compositional rather than theological reasons. In this case, therefore, our model retains too much ambiguity to provide for definite support of the claim.

The prestige metrics demonstrate interesting trends worthy of further exploration. Perhaps the most interesting trend relates to the growing popularity of female saints around 1300. Four of the five most popular saints in the corpus are female in the 1320s: Mary (0.79), Clare (0.49), Mary Magdalen (0.45), and Catherine of Alexandria (0.42). Given the close relationship between Clare and Francis, their frequent pairing, and the growing complexity of the panel compositions at the time, artists and patrons would certainly have sought out additional female saints to achieve balance.

And yet, some documentary evidence suggests that something more fundamental may have been operating. Shortly before his death in 1302, Cimabue was commissioned to paint a *Madonna and Child* that included Francis and Clare, and most likely Peter and Paul. Cook recognizes this as an extraordinary composition for the time:

Francis paired with Clare is common enough for panels designed for houses of Poor Clares. However, the figures of Peter and Paul in a Franciscan context are traditionally paired with Francis and Anthony of Padua; hence, they are the old and new apostles, the builders and rebuilders of the Church. Here, if Clare was substituted for Anthony, this is a bold claim for Francis and Clare as institution builders but also as apostles. (Cook, 1999, pp. 263-264).

If we compare Clare's previously stated prestige (0.53) during the period of her canonization in the 1250s to that (0.61) at the time this artwork was commissioned, we have some additional support for the bold claims of this panel's composition. Furthermore, we can see from the metrics that during the 1300s Clare's prestige outstripped Anthony's for the next two decades as well. As a final indicator of her prestige in this imagery, she maintains this high value even during the period of Louis of Toulouse's canonization. In this case, the prestige figures highlight a number of potential research areas including both specific research into the Poor Clares and their imagery and more general research themes such as the effect of the cult of Mary on the artwork of the period.

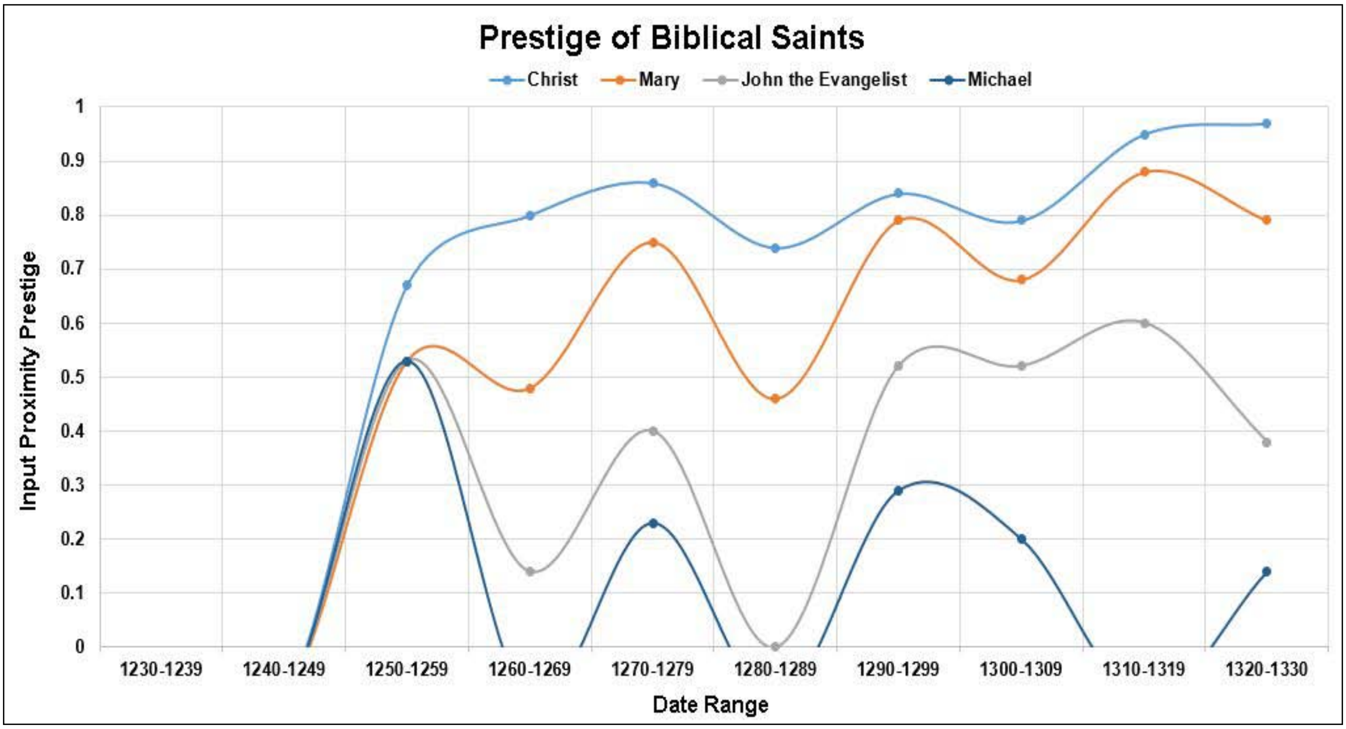

Figure 5 : Input Proximity Prestige of Biblical Saints

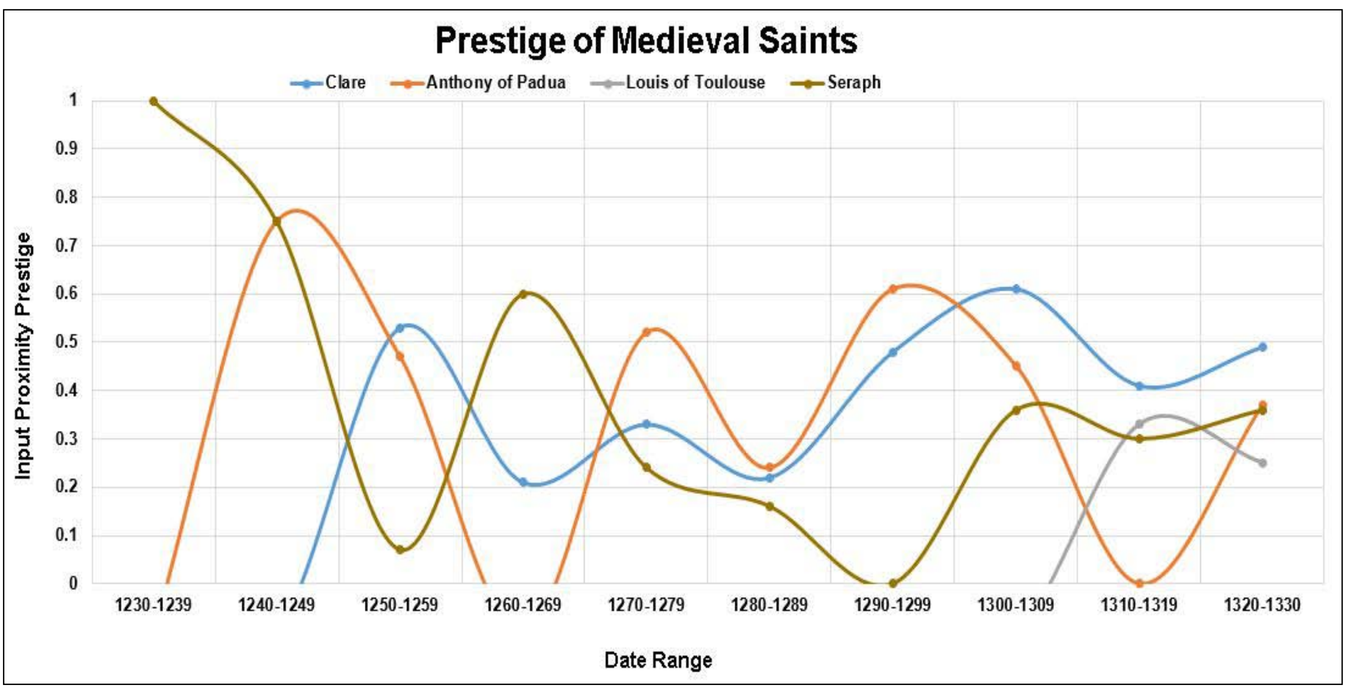

Figure 6 : Input Proximity Prestige of Medieval Saints

IV. Conclusion and Future Work

In general, the results of this study are encouraging and suggest that the techniques of distant reading currently applied to literary texts (Moretti, 2000; Michel et al., 2010) have a role to play in the study of iconographic images as well. Given the exciting possibilities of this approach, it makes sense to outline a few of the challenges of it particularly as it applies to medieval artwork before exploring its potential. In order for this type of research to make progress, researchers will have to address two different kinds of challenges. Studies of this kind suffer from several kinds of bias which can easily frustrate attempts to interpret data properly. Even if these issues of bias can be satisfactorily addressed, researchers will have to grapple with the persistent difficulty of data mining research in the arts and humanities (Sculley & Pasanek, 2008).

The field of data analysis often struggles with bias in data. Any common text in data mining or analysis will discuss items such as degrees of freedom, data standardization, random sampling and normally distributed data. These common issues, however, become worse when dealing with data sets derived from medieval artwork. For example, the survival rate of medieval paintings during this period was extremely low meaning that Researchers do not know if they have a representative sample of the artwork that was produced. Moreover, when this survival bias leaves only a few hundred works for study, the data derived from these surviving images will frustrate researchers' efforts to produce statistically significant results. Yet another technical challenge to working with such data revolves around the precise dating of medieval artworks (Polzer, 2005). In some cases, medieval artworks such as the *Pescia Dossal* are dated. In other cases, however, the dates are extraordinarily difficult to deduce specifically. It is not uncommon for dates to be expressed as a range spanning as many as 30 years. For the purposes of this study, we used, quite arbitrarily, the later date of any such time spans. We can foresee a good deal of future work in addressing these issues for data with these characteristics.

The broader issues of data mining in the arts and humanities so well articulated by Sculley and Pasanek (2008) are perhaps more serious than the specific issues with data. The results section of this work attempted to validate the technique in a number of ways and even attempted some hypothesis testing based on art-historical claims. Although we found a decent correspondence between the measures of structural prestige we used for our model and the questions we sought to address, the model demonstrated some ambiguity in our assessment of non-Franciscan portrayals of Francis. The ambiguity in the result of this test underscores Sculley and Pasanek's point that the standards for data mining in the humanities should be more difficult to meet than those in the sciences (2008, p. 422). We believe that their advice for adapting data mining to the needs of humanities research applies equally to research in the arts. Therefore, it seems reasonable for future research to attempt to replicate these results with other models and techniques (Sculley & Pasanek, 2008, p. 422). For example, we hope to replicate the results using different assumptions about the date ranges of paintings, i.e., rely on the early estimates of painting dates.

The most exciting way to address the issues of bias and data mining interpretation is to expand the scope of the study to include a broader cross-section of medieval art thematically, temporally and spatially. The images included in this study focus exclusively on Franciscan themes and iconography which necessarily limit its scope. In other words, Francis has an input proximity prestige of one in every period because his image is in every work. By expanding the scope of the study to include a more general corpus of medieval iconography researchers can validate the approach and expand their pool of research questions: Does the communion of saints as expressed in artwork with Dominican themes resemble that observed in Franciscan art? Do the saint pairings differ significantly from region to region? Does the popularity of a saint rise and fall in predictable patterns? With appropriate care, researchers may be able to answer such questions. In particular, we plan to expand the study by applying the technique to a large range of iconographic images selected from the Index of Christian Art (http://ica.princeton.edu/).

In our view, this approach may also contribute to a lively debate in the interpretation of medieval Italian art: the role of the Black Death in artistic production in Italy. With the publication of Millard Meiss's *Painting in Florence and Siena after the Black Death*, researchers have struggled with interpreting the artistic developments in Tuscany in the third quarter of the Fourteenth Century. Over 50 years after its publication, Meiss's work still inspires and challenges art historians to wrestle with the apparent discontinuity in artistic production before and after 1350 (Steinhoff, 2006). Given the results of this study, we believe that this technique could be adapted to bear on this debate. Our data reveal rapid swings in the relative prestige and pairing of saints that capture many salient points of development of the iconography of St. Francis. The Black Death and its devastating effects in Italy may well have forced patrons and artists negotiating intercessory imagery to search for new saints and arrangements of saints to meet their spiritual needs. The techniques outlined in this paper should make testing this hypothesis possible.

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