Chapter 5: Review, Revise, Requery: Reading Ekphrasis as/in a Dynamic Social Network

By Lisa Marie Antonille Rhody, December 2012

In her introduction to *Twentieth-Century Poetry and the Visual Arts*, Elizabeth Bergmann Loizeaux draws parallels between the ekphrastic situation and M. M. Bakhtin’s dialogic imagination, which he formulates in terms of the novel. Discourse, as Bakhtin describes it, consists of the flexible and reflexive relationships between language, as a form of social action and cultural production, and its object.

... between the word and its object, between the word and the speaking subject, there exists an elastic environment of other, alien words about the same object. Any concrete discourse (utterance) finds the object at which it was directed already as it were overlain with qualifications, open to dispute, charged with value, already enveloped in an obscuring mist— or, on the contrary, by the “light” of alien words that have already been spoken about it. It is entangled, shot through with shared thoughts, points of view, alien value judgments and accents. The word, directed toward its object, enters a dialogically agitated and tension-filled environment of alien words, value judgments and accents, weaves in and out of complex relationships, merges with some, recoils from others, intersects with yet a third group. (qtd. in Loizeaux 17)

Similarly, the ekphrastic poem, characterized by its responsiveness to another existing work of art, enters *in media res* into dynamic, on-going conversations, for example, between artists and their subjects or between other poets and the same work of art, or between curators and art historians and the work of art. Loizeaux argues that the social and technological developments of the twentieth century in the form of the public museum and electronic reproduction energize the ekphrastic situation with a sense that ekphrasis (particularly regarding more popular works such as Van Gogh’s *The Starry
Night) enters into an already-lively conversation about the visual work of art. As she explains further on:

…ekphrases often carry on exchanges with other ekphrases (as well as with art-historical commentary) as both engage the work of art: a poet represents the work of art in response, in other words, not just to the work of art but to other representations of it, and in doing so crafts an “answer” to those implicit members of the audience. (17)

Loizeaux, therefore, redefines ekphrasis as a poetic genre that in the twentieth century is purposefully, necessarily, and often self-consciously dialogic, and consequently, I further argue that understanding twentieth-century ekphrasis requires a means by which it can be dynamically contextualized as/in an ongoing, historical social network of other poems, poets, artists, art critics, and readers.

The following chapter builds on Loizeaux’s assertion that the social and dialogic nature of ekphrasis requires that our critical understanding of it be contextualized within a flexible network of discourses, and I propose a methodology for discovering forms of discourse through topic modeling that can also be visually rendered and interpreted with network analysis. Leveraging the computational strengths of an algorithm such as latent Dirichlet allocation (hereafter LDA) to detect latent patterns of language across a corpus of hundreds or thousands of poems and examining the composition of LDA topics as an effective method for considering literary discourse, this chapter reads “at a distance” ekphrastic poetry within a small collection of only other ekphrastic poems and ekphrastic poetry within the context of thousands of other poems.

The chapter is organized as an exploration of how LDA detects latent patterns in corpora of poetic texts and how literary scholars can use LDA as a methodological intervention into the study of ekphrasis. In the first section, I explain the assumptions
made by the LDA algorithm as it explores a large corpus of texts and then further
particularize the differences between topics created from articles in *Science* magazine and
topics created from corpora of poetry. Identifying how the differences between the kinds
of texts modeled produce different kinds of topics, I then present an interpretive strategy
that depends upon the coordinated and telescopic vacillations between close and distant
readings to best respond to the unique challenges figurative language texts present for
LDA. Building from an identification of LDA topics as forms of discourse that depend
on close readings in order to evaluate the effectiveness of the model, I then present two
case studies that use the “forms of discourse” understanding (articulated in terms of what
I call semantically evident and semantically opaque topics) to read a set of 276 ekphrastic
poems. Reintroducing the use of NodeXL, previously introduced in chapters 2 and 3, as
a social network analysis and graphing tool, I demonstrate visualizations of relationships
between documents and topics, topics and other topics, and groups of documents
clustered by the degree to which poems draw their language from each topic. By
situating poems within networks of other poems that draw from similar discourses, I
reconsider the ekphrastic tradition as representative of a plurality of attitudes toward the
visual arts. Similarly, I gesture towards purposefully provocative avenues for future
research that reconsider women’s contributions to the ekphrastic tradition. Throughout
the chapter, methodological readjustments to the aperture of the LDA model as critical
lens—transitions from distant to close readings—inform our understanding of ekphrasis
as inherently dialogic, dynamic, and polyvocal.

As this project is particularly concerned with women’s contributions to the
ekphrastic tradition, the examples in the following pages focus on women’s ekphrastic
poems as they engage with other poems closely associated with similar LDA topics. Each example is considered as a unique engagement between a specific poet, aesthetic work, and set of discourses, understood as topics, rather than a totalizing commentary on ekphrastic poetry by women in general. Instead, each close, networked reading is meant to be suggestive of the variety and diversity of possible engagements between women poets and poetic discourses that inform our assumptions about the genre and to further complicate and enrich what we understand as the genre’s tradition and canon. The examples here are purposefully provocative, gesturing toward a way of accessing and reconsidering the ekphrastic tradition that privileges understanding individual poems as responding to and influenced by other poems participating in similar discourses to potentially widely ranging effect. Thus, in this chapter, I also demonstrate through example that employing advanced technologies at scale (which is to say across a large dataset of hundreds or thousands of poems) requires a clear argument as to how humanists closely “read” detailed visualizations of humanistic texts and how we must understand, adapt, and critique methodologies developed by computer scientists that provoke results appropriate to individual humanities disciplines and data. Considering individual poems as inextricably part of a larger network of discourses insists upon readings that are also performed in relationship to a diverse collection of poems participating in similar discourses.

**Why use LDA to study ekphrasis?**

LDA is a particularly useful way to explore the canon and tradition of ekphrastic poetry because both LDA and definitions of ekphrasis as a genre presuppose that there are latent patterns of language that when discovered characterize the group as a whole.
Ekphrasis as a genre of poetry is characterized by tropes, which tend to reoccur throughout the canon. With regard to twentieth-century ekphrasis, Loizeaux, for example, points to the way in which poets invoke museums as sites of display and as indicative of poets’ anxieties about how museums act as interpretive forces. She also points to the impulse to narrate the work of art, to the poets’ tendency to act as guide or instructor, and to craft an imaginary voice on behalf of the work of art. Understanding and interpreting poems in terms of they participate in the tradition of ekphrasis, then, becomes a matter of discovering how poets enter into, disrupt, or perpetuate the ongoing discourses associated with the tropes that typify the genre.

The use of LDA as a method of discovery and as a means of understanding the contents of large corpora of texts begins with a similar set of assumptions. First, LDA assumes that text documents in large corpora tend to draw from categories of language that are associated with the subjects of those documents. In an effort to discover the semantic composition of a large collection of text documents, LDA calculates the likelihood that words that refer to similar subjects appear in similar contexts, and then the LDA algorithm groups those words into “topics.” LDA, then, presupposes that we can discover the semantic composition of a corpus by discovering the “topics” from which each individual text document draws its language.

Following in the vein of Matthew Jockers, Ted Underwood, Scott Weingart, and others who have published gentle introductions to topic modeling for humanists, I want

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103 For other gentle introductions to LDA for humanists, see Matthew Jockers’s blog post “The LDA Buffet is Now Open; or, Latent Dirichlet Allocation for English Majors” and Scott Weingart’s blog post “Topic Modeling for Humanists: A Guided Tour.”
to begin conversation about LDA in this chapter with a short, if potentially reductive narrative of how LDA generates topics from text corpora that I will return to throughout the chapter to guide discussion of how the LDA algorithms produce topic models of poetry.

Imagine that there is a farmer’s market on the other side of town. Many of your neighbors rave about the quality of the produce, but you would like to know what kinds of produce are sold there before you decide to drive across town to try it out. Your neighbors leave for the market with empty baskets and return with full baskets. Assuming that your neighbors only chose from the kinds of produce available at the farmer’s market and that there is a limited variety of produce available, each neighbor selects produce from the available choices that they like the best. Since it happens to be late summer, your neighbors select early Gala and Granny Smith apples, butternut squash, Bosc pears, and one neighbor even snatches up the last pint of blueberries. One by one as your neighbors arrive home, you survey the baskets’ contents. As you look into more and more baskets, your predictions about what produce is available at the farmer’s market becomes clearer. Examining the quantities and varieties of produce in each basket, you could begin to predict not only the range of produce that might be awaiting you at the farmer’s market but also the relative quantities. You happen to know that this particular farmer’s market guarantees that there will be 10 kinds of produce available each week, and over the course of sampling your neighbors’ baskets, you come to the conclusion that the selection of produce at the farmer’s market consists of 20% green apples, 20% red apples, 15% pears, 10% winter squash, 10% cantaloupe, 5% corn, 5% beans, and 2.5% tomatoes and 2.5% assorted other kinds of produce that were
different enough from one another that it makes sense to just call them miscellaneous. As more neighbors arrive, with baskets to examine, you can refine your predictions about what the available selection of produce might be at the farmer’s market.

In the case of the farmer’s market, your approach to predicting the 10 kinds of produce and the available quantities of each based on the contents of your neighbor’s baskets is akin to the way LDA algorithms approach texts. LDA assumes that documents are like your neighbor’s baskets. Authors, like your neighbors, select from a limited number of available kinds of words called “topics” in order to produce their documents, in this case poems. Each author chooses to varying degrees how much of each kind of topic they use for each document; however, the number of total available topics, just like the total number of kinds of produce remains constant. LDA attempts to describe the overall distribution of topics in a collection of texts in the same way that you discovered the kinds and quantities of produce at the market. The size of the “topics” likewise reflects your estimation of how much of each kind of produce is available. You were able to predict that there were more apples and pears at the market than there were blueberries and tomatoes because across the whole sampling of baskets there were more apples and pears and fewer blueberries.

There is one significant difference, however, between the human topic model example and the algorithm. LDA does not produce names for the topics it discovers or sort words with an understanding for what words mean. Consider that while you are sorting through baskets, you come across an Asian pear, but you’ve never seen an Asian pear before. The Asian pear was in a basket with a large number of apples and pears. You make note of that, set it to the side, and continue to sort through baskets. Over the
remaining baskets, Asian pears tend to appear in other baskets where there are also other kinds of pears. As a result, you come to the conclusion that, since Asian pears frequently appear in baskets with other pears, the Asian pear in each future basket should be sorted with the pears. This method of determining how to sort Asian pears reflects the manner in which LDA assigns words to topics, according to the other words that are found in the same document. Although the algorithm cannot account for what words mean, much like your method of discovery about Asian pears, LDA does a surprisingly good job of sorting words based on co-occurrence and proximity. Finally, LDA sorts words into topics based on prior knowledge that there are a definite number of topics in the overall corpus—much the same way that you knew to look for 10 types of produce.\footnote{The process by which the number of topics to tell the model to use is not, as of yet, a standardized procedure. The measure for the “right” topic number is often derived through trial and error. After starting with one number (usually between 40 and 60) one determines how “actionable” and “coherent” the topics that the model produces are, adjusting up and down in subsequent iterations until there is agreement that the best model has been produced.}

Topic models (and LDA is one kind of topic modeling algorithm) are generative, unsupervised methods of discovering latent patterns in large collections of natural language text: generative because topic models produce new data that describe the corpora without altering it; unsupervised because the algorithm uses a form of probability rather than metadata to create the model; and latent patterns because the tests are not looking for top-down structural features but instead use word-by-word calculations to discover trends in language. David Blei, credited with developing probabilistic topic modeling methods, describes topic models the following way:

\begin{quote}
Topic models have been developed with information engineering applications in mind. As a statistical model, however, topic models should be able to tell us something, or help us form a hypothesis, about the data.
\end{quote}
What can we learn about the language (and other data) based on the topic model posterior? (Blei “Introduction” 84)

Blei stages topic models as an ex post facto method for testing assumptions about natural language data. In other words, once a collection has been created, LDA is designed to test our assumptions about what topics are discoverable. The type of discoveries that are possible with LDA seem viable ways to approach ekphrastic poetry given our understanding of it as a genre in which the language frequently returns to the eternal stillness of the image, prompts reflectiveness about historical location and memory, creates imagined voices for the art objects, or narrates the image. Furthermore, in Heffernan’s words, “Ekphrasis… turns on the antagonism—the commonly gendered antagonism—between verbal and visual representation.” Could topic models detect gendered language, tropes, or the language of stillness in ways that “we can learn” about the genre more broadly? This is the question which began “Revising Ekphrasis,” a digital topic modeling and corpus discovery project I developed that uses digital and computational tools to explore ekphrastic and non-ekphrastic poetry. The topic models described in this chapter represent only two of the experiments that have become part of the digital project. I have chosen these for two reasons: first, to propose a methodology for using LDA to explore and test assumptions about poetic tradition, genre, and canon formation; and second, to demonstrate how LDA provokes new questions about the ekphrastic tradition in ways that are more inclusive and broadly conceived than previous methods. Few questions will find “answers” here. Instead the hope is to uncover new approaches to address enduring humanities questions while at the same time expanding the range of possible questions we might fruitfully ask.
LDA topics and poetry

As was discussed in chapter 4, topic modeling is a form of text mining developed in response to the growing challenge of managing, organizing, and navigating large, digitized document archives, and coincidentally, topic modeling has also been developed with primarily non-fiction corpora in mind. One of the most notable early uses of LDA by Blei explores a digitized archive of Science. Other examples of topic modeling have used Wikipedia, NIH grants, JStor, and an archive of Classics journals. As literary scholars well know, however, poems exercise language in ways purposefully inverse to other forms of writing, such as: journal articles, encyclopedia entries, textbooks, and newspaper articles. Therefore, it is reasonable to predict that there will be differences between LDA models of poetry and models of non-fiction texts. In terms the non-figurative language found in topic models of the journal Science, Blei explains that topics detect thematic trends across texts:

We formally define a topic to be a distribution over a fixed vocabulary. For example, the genetics topic has words about genetics with high probability and the evolutionary biology topic has words about evolutionary biology with high probability. (Blei “Introduction” 78)

Presented as a method of discovery and description, computer scientists see topics as revealing latent thematic trends that pervade large and otherwise unstructured text corpora, and with respect to the data used to create the topic model, this conclusion makes sense. Since the datasets used to develop and refine topic modeling algorithms have been non-figurative language texts, the assumption that there is a direct semantic relationship between words that are frequently found within close proximity of one

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another. Blei’s illustrative example of how the probabilistic topic model works in *Science* is the most accessible explanation thus far for humanists. Therefore, in order to compare how LDA creates topics in non-figurative texts (*Science*) versus how topics are generated from a corpus of poetry, I must first explain how the topics in Blei’s model of 100 topics across 17,000 *Science* articles are created, using two of Blei’s illustrations.

Next, I will create a parallel example using Anne Sexton’s poem “The Starry Night” from a 60 topic model of 4,500 poems from the “Revising Ekphrasis” dataset, pointing to how topic models estimate topic proportions in documents and how topic keyword distributions in poetry are not “thematic” in the way that topic models of non-fiction documents are.

In “Probabilistic Topic Models,” Blei uses two illustrations to explain how topic modeling of a large, digitized collection of *Science*. The first illustration depicts an excerpt from one article within the collection titled “Seeking Life’s Bare (Genetic) Necessities” and demonstrates the relationship between topics and keyword distributions. The first illustration in Figure 38 uses the colors yellow, pink, green, and blue to represent four of the topics the model predicts exist in the dataset. These are the “kinds of produce” from the opening farmer’s market example. On the far right hand side is a bar graph which represents the proportions of the yellow, pink, and blue topics the model predicts are in the document (an article in this case). The largest topic in the document is yellow followed by pink then blue. The lines from the bar graph on the far right point to the places in the text where words that are associated with the yellow, pink, and blue topics can be found in the document. Essentially, the histogram is showing the equivalent of there being more apples than pears or grapes in a single basket. On the far
left hand side are the first three words of the topic keyword distribution. Those represent the “kinds of words” that could be found in the places in the text that are highlighted in yellow, pink, and blue.

Figure 38: Illustrative example of Science topic model (Blei “Introduction” 78)

The graphic in Figure 38 helps to identify how the topic proportions (like the number of apples in a basket of produce from the market) correlate to individual words in the document (highlighted above in yellow, pink, and blue), which then comprise the “topic” keyword distributions which are displayed at the far left as a partial list of keywords.  

106 Introduced in chapter 4, each topic (kinds of produce) is composed of the words (fruit) in the document (basket). Topic keyword distributions are where the human task of interpreting what the model has done with the dataset begins.
Figure 38 is an illustrative example, meaning the document and topic assignments in the graphic are not actually derived from a specific model; however, in a second graphic, Blei continues to explain the how “Seeking Life’s Bare (Genetic) Necessities” appears within a 100 topic model of 17,000 Science articles. In Figure 39, Blei represents the probability of each topic using a histogram (bar graph) that demonstrates the relationship between the topics 0-99 (along the horizontal axis) and the probability (as a decimal along the vertical axis) that the topic is found in “Seeking Life’s Bare (Genetic) Necessities.” Some topics have higher probabilities of appearing in the document than others, as represented by the taller bars in the graph. On the right side of the graphic, the topic keyword distributions are listed vertically in columns. At the top of each column is a bolded word surrounded by quotation marks that serves as a label created by Blei to describe the words in the topic and demonstrating Blei’s rationale for claiming that topics are thematic. For example, the topic labeled “Genetics” is predicted by LDA to be the largest topic in the document in much the same way that in the farmer’s market analogy you could determine that the largest produce type in a single basket was from the topic “apples.” In that light, the model’s prediction about “Seeking Life’s Bare (Genetic) Necessities” makes sense. We would normally expect the words human, genome, dna, genetic to be found in articles about “genetic necessities.” By glancing over the words in the topic keyword distributions, we gather together a sense of what the article might be about.
Surveying Blei’s list of key terms in each topic clarifies the way in which models predict thematic trends in large text corpora. The sense that each of the words in each of the columns belong together makes an impressionable argument for LDA’s ability to use Dirichlet allocation to sort large collections of documents into topical categories. By affixing the term “latent” to the statistical model (latent Dirichlet allocation), as Blei explains, foregrounds the expectation that topic modeling is meant to discover hidden, recognizable patterns within the large collection of texts. It would take even the most proficient reader an extraordinary period of time to read 17,000 articles from *Science*. Therefore, while we know through disciplinary familiarity and deduction that these are likely topics to be found throughout the journal’s publication, we wouldn’t be able to detect by human reading, or even planning, what that distribution would be. Blei,
therefore, concludes that probabilistic topic modeling “provides a powerful tool for
discovering and exploiting the hidden thematic structure in large archives of text”
(“Introduction” 82).

Unsurprisingly, humanists interested in sorting, sifting, and organizing large
collections of text, managing large document archives, and creating better browsing
options for digital libraries find LDA’s potential exciting and promising. Additionally,
humanists interested in uncovering the “latent patterns” in large datasets are also
enthused about the algorithm’s potential for exploratory studies. Most notably, Robert
Nelson’s project “Mining the Dispatch” employs LDA to uncover hidden patterns within
the archives of the Richmond Daily Dispatch just before, during, and after the Civil War.
Nelson’s LDA analysis uses the topic distributions over thousands of Dispatch articles
over the course of the war to track relationships between increases in military draft and
fatalities and the patriotic rhetoric. Even more impressively, Nelson’s utilization of LDA
is more than a descriptive endeavor, moving from topic distributions to argue that the
rhetoric of nationalism shifts in the Confederate South during the Civil War in
relationship to casualty rates and calls for enlistment.\(^{107}\) Nelson’s work in this area
represents one of the most ambitious and successful projects to date in the humanities that
uses probabilistic topic modeling. Mining the Dispatch broaches the territory of
figurative language in its analysis of patriotic discourse in Civil War Confederate
newspapers. A strong correlation exists between increase in patriotic language that
glorifies fighting on behalf of the Confederate states and the numbers of poems appearing

\(^{107}\) For more information on how LDA has been used by humanists to detect changing attitudes toward
patriotism ad nationalism, see: Nelson, Robert K. Mining the Dispatch.
in the newspaper at the same time. In Nelson’s project, poetry is combined with opinion articles and political and agricultural reports, and the composition of the dataset allows the poetic texts to map well with its prose counterparts.

However, topic models of purely figurative language texts like poetry do not produce topics with the same thematic clarity as those in Blei’s topic model of *Science* or even Nelson’s model of the *Richmond Daily Dispatch*. And the literary scholar has good reason to be skeptical about the results of LDA analysis when dataset to be explored includes primarily, if not exclusively, poetic texts. Whereas scholarly articles and books strive for clarity and avoid ambiguity, poetry specifically uses language’s ambiguity. So, should the same standards for evaluating topic models of non-figurative language texts guide the principles we use to evaluate the accuracy of topic models of figurative language collections? How would they differ?

In general, the guiding factors for text mining generally and topic modeling specifically are to generate *actionable* and *comprehensible* results.

**Actionable:** Results should be consistent and reproducible, which means that the model could also be used to make predictions about new data added to the dataset. Of course, whether or not results are indeed actionable depends to a large extent on the ability to find a fair and measurable degree of success. Actionable results require that researchers are clear about their *a priori* assumptions and the composition of the dataset and the predicted degree to which the results might be found reliable.
Comprehensible: For the results of text mining to be useful, humans need to be able to read, to understand, and to interpret them. Frequently, in topic modeling comprehensible results are understood to be thematic or semantically meaningful. In other words, when reading key word distributions, it is usually obvious that there is a thematic array that humans can read and interpret sensibly. For example, in Blei’s keyword distributions the terms “evolution, evolutionary, species, organisms, life, origin” lead to a comprehensible thematic topic: evolution.

Herein lies the rub for texts as highly figurative, purposefully ambiguous, and semantically rich as poems. Returning once again to Blei’s article, he writes: “The interpretable topic distributions arise by computing the hidden structure that likely generated the observed collection of documents.” In a footnote, Blei clarifies his claim:

Indeed calling these models “topic models” is retrospective—the topics that emerge from the inference algorithm are interpretable for almost any collection that is analyzed. The fact that these look like topics has to do with the statistical structure of observed language and how it interacts with the specific probabilistic assumptions of LDA. (Blei “Introduction” 79)

The topics from Science read as comprehensible, cohesive topics because the texts from which they were derived aim to use language that identifies very literally with its subject. The algorithm, however, does not know the difference figurative and non-figurative language. So the process LDA employs does not change: topics remain a distribution of words over a fixed vocabulary, which is to say all the words that make up the dataset upon which the LDA algorithm is run. Therefore, the first stage of a topic modeling
experiment with poetry requires determining what *comprehensible* means in topics generated from poetry corpora and whether or not the resulting models can be “actionable.”

The following example serves as a parallel, illustrative example to Blei’s but this time demonstrating how LDA “reads” a sample poem—Anne Sexton’s “The Starry Night.” To create the illustration, I used MALLET, a software environment introduced in chapter 4, to create a 60 topic LDA model using a dataset of 4,500 poems from the “Revising Ekphrasis.” When the collection of poems was prepared for the experiment, the MALLET default stoplist removed words considered to be too numerous such as articles, frequently used pronouns, conjunctions, prepositions, and pronouns. Recalling to mind the farmer’s market example from earlier in this chapter, “The Starry Night” is an example of what one neighbor’s basket of produce (poem/document) might look like. In the basket, 29% of the produce (words) would be like apples (Topic 32), 12% of the produce would be corn (Topic 2), and 9% of the produce would be like grapes (Topic 54).\(^\text{108}\) All in all, 50% of the basket (poem/document) can be accounted for by three produce types (topics).\(^\text{109}\) For simplicity’s sake, I have ignored the smaller topics and focus just on the top three topics. In order to simulate to some degree the way in which the topic model “reads” the poem, I have crossed out words that would be removed by the stoplist, and highlighted in green (Topic 32), yellow (Topic 2), and blue (Topic 54).

In Table 1, which directly follows the poem, there are three columns that list the topics from which “The Starry Night” is predicted to draw most heavily. In each column

\(^{108}\) The words “poem” and “document” throughout the remainder of the chapter are used interchangeably because, as was mentioned in chapter 4, the dataset consists of individual poems saved as individual plain text documents that include only the title and body of individual poems.

\(^{109}\) The sum of the three top document probabilities: \(29+32+12=50\)
of the table, the number of the topic is listed at the top next to the probable proportion of the document that uses words from this topic. The fifteen words below each Topic number represent a sampling of the word distribution that makes up the whole topic. For example, in the farmer’s market example the topic with the largest percentage would be “apples.” Under the “apples” topic, we might find Macintosh, Fugi, Honeycrisp, and Gala, all words associated with apples. For the purpose of making the assignment of words from the poem to the topic keyword distributions clear, each topic has been assigned a color (green/32, yellow/2, blue/54). Words in the text of “The Starry Night” that are associated with topics 32, 2, and 34 are highlighted in a corresponding color.  

The Starry Night

That does not keep me from having a terrible need of—shall I say the word—religion.

Then I go out at night to paint the stars. Vincent Van Gogh in a letter to his brother

The town does not exist

except where one black-haired tree slips

up like a drowned woman into the hot sky.

The town is silent. The night boils with eleven stars.

Oh starry starry night! This is how

I want to die.

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110 Again, to be clear, the keywords in each topic are derived from all the documents in the set of 4,500 that the LDA considers to be part of the topic, so there will be more words in the key word distributions than there are in “The Starry Night.” The model assumes that words in the key word distribution are often found in the context of other words also listed in the key word distribution.
It moves. They are all alive.

Even the moon bulges in its orange irons
to push children, like a god, from its eye.

The old unseen serpent swallows up the stars.

Oh starry starry night! This is how
I want to die:

into that rushing beast of the night,
sucked up by that great dragon, to split
from my life with no flag,
no belly,
no cry.

Table 9: Key word distributions generated by a 60 topic model of 4500 poems (Note: Keywords in this table are representative of the entire model, not just "The Starry Night."

<table>
<thead>
<tr>
<th>Topic 32 (29%)</th>
<th>Topic 2 (12%)</th>
<th>Topic 54 (9%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>night</td>
<td>death</td>
<td>tree</td>
</tr>
<tr>
<td>light</td>
<td>life</td>
<td>green</td>
</tr>
<tr>
<td>moon</td>
<td>heart</td>
<td>summer</td>
</tr>
<tr>
<td>stars</td>
<td>dead</td>
<td>flowers</td>
</tr>
<tr>
<td>day</td>
<td>long</td>
<td>grass</td>
</tr>
</tbody>
</table>
Once the model generates the topics, human interpretation begins. At first, Topic 32 and 54 appear similar to the coherent, thematic topics in the topic model of Science. Topic 32 includes words that could fall under the rubric of “night,” and the words in Topic 54 could be described as the “natural world.” We might be tempted based on this first read to assign the topic labels “night” and “natural world” in the same way that Blei labels topics from Science as “genetic” and “evolution;” however, as I will discuss further on, those labels and the assumption that the topics are “thematic” in the same way as Blei’s would be incorrect. For example, the night and natural world of “The Starry Night” are actually painted representations of those concepts, and consequently, it would be misleading to say that the poem is, strictly speaking, about night and the natural world in the same way that the article from Science is about genetics and evolution. I will
return to this idea further on, but for now it is safe to say that those categories do not appear to be different.

Topic 2, on the other hand, does not have the same unambiguous coherence that 32 and 54 do: the words in Topic 2 are more loosely connected. It would be tempting to read the topic as having to do with death, but we would do that because our reading of “The Starry Night” predisposes us to consider it that way. There are “intruder” words in this category. By looking solely at the words in the list and not taking into consideration “The Starry Night,” words such as long, world, and day are not necessarily words we might classify as “death” words in the strictest sense. In fact, topic intrusion is one way in which computer scientists have begun to develop a method for evaluating and interpreting topic models. In “Reading Tea Leaves: How Humans Interpret Topic Models,” Jonathan Chang, Jorden Boyd-Graber, Sean Gerrish, Chong Wang, and David Blei suggest methods for measuring the “interpretability of a topic model.” The authors present two human evaluation tests meant to discern the accuracy of models by using the keyword distributions (the kinds of produce at the farmer’s market), and the topic to document probabilities (the proportion of kinds of apples compared to how many fruit are in each basket)—called word intrusion and topic intrusion tests respectively. Word intrusion tests involve selecting the first eight or so words from each topic and adding one word each list for a total of nine words. Human subjects (generally disciplinary experts) were then asked to determine which word in each group did not belong. Chang, et al. discovered that with relative high success, human readers could discern a thematic connection between terms to reliably distinguish the one out-of-place
term. As a result, the authors suggest that word intrusion tests measure “how well the inferred topics match human concepts” (6).

Topic intrusion tests presented human subjects with topic labels (like apples, pears, and corn are labels for the “kinds of produce” that might be at the farmer’s market); the words most likely to be associated with each topic (such as Macintosh, Gala, Fuji, and Honeycrisp), and the top documents associated with each topic (basket #1, basket #2, basket #3, for example). Then, one document (a basket unlike any of the others) that does not belong in the group, the “intrusion,” is then added to the set. Human subjects were then asked to identify which document did not belong, which they could do with reasonable accuracy.

For the purposes of modeling poetry data, word intrusion would not be as effective a method for determining a model’s accuracy at categorizing documents or detecting latent patterns unless the specific changes that happen to the nature of topic distributions for poetic corpora are adjusted for. In other words, topics from the models in my project were not easily interpreted by keywords alone, and yet the results are still useful. I discovered that topic models of poetry do have a form of coherence, but the coherence is different than in topics of non-fiction texts. My research confirms, to a degree, Ted Underwood’s suspicion that topics in literary studies are better understood as a representation of “discourse” (language as it is used and as participates in recognized social forms) rather than a thematic string of coherent terms.\(^{111}\) Topic models of poetry

\(^{111}\) I qualify this statement out of recognition that the document types Underwood is modeling are volumes as opposed to individual poems, which may have effects on the degree of reliability with which one can make the comparison. For more on conversations between Ted Underwood and I regarding topics as forms of discourse, see Underwood, Ted. “What Kinds of ‘topics’ Does Topic Modeling Actually Produce?” and Rhody, Lisa. “Chunks, Topics, and Themes in LDA.”
do not reflect the anecdotal evidence that LDA frequently leads to semantically meaningful word distributions. Instead, topic models of the “Revising Ekphrasis” dataset created four consistently recurring types of topics. Moreover recognizing the following four types of topic coupled with close reading of samplings of documents containing each “topic,” which allows a literary scholar to see coherence in topics as forms of discourses, worked much better for determining whether or not the results of the model were actionable and comprehensible. “Intruders” as individual words does not work for LDA topics of poetry because poems purposefully access and repurpose language in unexpected ways; however, when viewed as forms of discourse, topics can be reconsidered in light of whether or not close readings show that individual documents are entering into a form of discourse for a thematic purpose.

LDA topics of a model of the poetic documents in the “Revising Ekphrasis” dataset return one of four types of topic, which I define as follows:

1.) OCR\textsuperscript{112} and other language or dialect distinctive features\textsuperscript{113} – These topics represent, for example, errors that occur in the optical character recognition scanning process used when turning print documents into digitizing texts, for example substituting “com” for “corn.” The most common OCR errors have been filtered out through a preprocessing technique that searches for such errors and fixes them; however, machines aren’t perfect and some of these features remain in the final dataset. Their presence may sort out as if they were features of another language.

More commonly in this dataset, however, one or two topics form around an

\textsuperscript{112} OCR – Optical Character Recognition software visually changes scanned print pages into digitized text.

\textsuperscript{113} Topic modeling is frequently used to help discover information in a variety of languages. I choose “other” rather than “foreign” here, since not all “other” languages would be for all researchers “foreign” ones.
approximate 1% of the data that includes foreign language terms or the original form of a poem before its English language translation. The following two topic examples found in the same topic model as “The Starry Night” demonstrate how the model clusters these:

Topic 8: de la Gertrude el en green le din miss con yo verde inside da taint

Topic 39: ye night wi ha auld merry Tomlinson syne sin rats gat mayor

Similarly, topics can also be created by grouping together distinctive dialects and languages other than English. We will not be considering these topics in detail other than to point out that they exist.

2.) Large “chunk” topics – Longer or extended poems that outsize the majority of other documents in the subset pull one or more topics toward language specific to that particular poem. For example, the keyword distribution for Topic 12 includes terms such as: bongy, yonghy, bo, lady, jug, order, jones and jumblies. These are words that are repeated frequently in the extended poem “The Courtship of the Yonghy-Bonghy-Bo” by Edward Lear and demonstrate how one poem with high levels of repetition can pull a topic away from the rest of the corpus, along with other poems with high frequency repetitions of particular phrases. In the case of Topic 12, the poems included in the topic and shown in Table 2 tend to be longer and to include greater incidence of repetition. It is possible that these poems share thematic affinities, but the strength of those affinities have more to do with linguistic structure than meaning. In Table 2, the documents with the highest probabilities of drawing a large proportion of their words from Topic 12 are listed in descending order. Under
the “Topic 12” label are the probable proportions for each document expressed in decimals. In the second column are the corresponding poem titles.\textsuperscript{114}

Table 10: Titles of poems in the "Revising Ekphrasis" dataset with the highest probable proportion of Topic 12, listed in descending order.

<table>
<thead>
<tr>
<th>Topic 12</th>
<th>Poem Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.680665</td>
<td>The Courtship of the Yonghy-Bonghy-Bo</td>
</tr>
<tr>
<td>0.590501</td>
<td>Choose Life</td>
</tr>
<tr>
<td>0.504747</td>
<td>Zero Star Hotel [At the Smith and Jones]</td>
</tr>
<tr>
<td>0.501921</td>
<td>The Midnight [For here we are here]</td>
</tr>
<tr>
<td>0.47986</td>
<td>Earthmover</td>
</tr>
<tr>
<td>0.462247</td>
<td>Invitation to the Voyage</td>
</tr>
<tr>
<td>0.412626</td>
<td>Mr. Macklin's Jack O'Lantern</td>
</tr>
<tr>
<td>0.358385</td>
<td>The Steel Rippers</td>
</tr>
<tr>
<td>0.333965</td>
<td>The Cruel Mother</td>
</tr>
<tr>
<td>0.276595</td>
<td>Vacant Lot with Pokeweed</td>
</tr>
<tr>
<td>0.274312</td>
<td>Lullaby of an Infant Chief</td>
</tr>
<tr>
<td>0.253223</td>
<td>The Jumblies</td>
</tr>
<tr>
<td>0.250493</td>
<td>American Sonnet (35)</td>
</tr>
<tr>
<td>0.230571</td>
<td>Rückenfigur</td>
</tr>
<tr>
<td>0.221246</td>
<td>Two Poems</td>
</tr>
<tr>
<td>0.217995</td>
<td>The Lady of Shalott</td>
</tr>
<tr>
<td>0.2177</td>
<td>Mr. Smith</td>
</tr>
</tbody>
</table>

\textsuperscript{114} When the model outputs the probable proportions for each poem, it expresses that proportion in a decimal. When possible in my discussion of a topic, I convert the decimal to a percentage because that expression of proportion seems more appropriate and avoids statements such as “Rukenfigur” is predicted to contain .23 of Topic 12; however, when I list document probabilities as they have been produced from the model, those same numbers are expressed as decimals.
3.) *Semantically evident topics*—Some topics do appear just as one might expect them to in the 100-topic distribution of *Science* in Blei’s paper. Topics 32 and 54, as illustrated above in Anne Sexton’s “The Starry Night,” exemplify how LDA groups terms in ways that appear upon first blush to be thematic as well. As I mentioned earlier, though, the illusion of thematic comprehensibility obscures what is actually being captured by the topic model. The way in which we interpret semantically evident topics like 32 and 54 must be different from the semantically coherent topics of non-figurative language texts. It is more accurate to say that Topics 32 and 54 participate in discourses surrounding that “night” and “natural landscapes” in Anne Sexton’s “The Starry Night.”

As Loizeaux points out in *Twentieth-Century Poetry and the Visual Arts*, Sexton is entering into an ongoing conversation with other confessional poets about madness and artistic genius by engaging in language that refocuses collective attention on a widely-recognized work of art with a recognized connection to another artist suffering from mental duress.115 She enters into that discourse through the other surrounding discourses that include night and natural landscape. It would still be incorrect to say that 29% of the document is “about” night, when what Sexton describes is a *painting* of a night sky and natural landscape. As literary scholars, we understand that Sexton’s use of the tumultuous night sky depicted by Vincent Van

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Gogh provides a conceit for the more significant thematic exploration of two artists’ struggle with mental illness. Therefore, it is important not to be seduced by the seeming transparency of semantically evident topics. Even though the topics appear to have a semantic relationship with the poems because they appear so comprehensible, it is important to remember that semantically evident topics form around a *manner* of speech that reflects quite powerfully the definition of discourse described by Bakhtin earlier in the chapter that “between the word and its object, between the word and the speaking subject, there exists an elastic environment of other, alien words about the same object.” The significant questions to be asked regarding such topics when interpreting LDA topic models have more to do with what we learn about the relationships between the ways in which poems participate in the discourses that the topic model identifies. Word intrusion tests (the kind suggested by Chang, et. al. as a measurement of a model’s accuracy) may still work with semantically evident topics because semantically evident topics mirror the thematic comprehensibility of topics from models of non-figurative language; however, there are naturally occurring word intrusions that may not affect the efficacy of the topic distributions, and these would require deeper human interpretation before just throwing them out.

4.) *Semantically opaque topics*—Some topics, such as Topic 2 in “The Starry Night,” appear at first to have little comprehensibility. Unlike semantically evident topics, they are difficult to synthesize into the single phrases simply by scanning the keywords associated with the topic. Semantically opaque topics would not pass the intrusion tests suggested by Chang, et. al. because even a disciplinary expert might
have trouble identifying the “intruder” word as an outlier. Determining a pithy label for a topic with the keywords, “death, life, heart, dead, long, world, blood, earth…” is virtually impossible until you return to the data, read the poems most closely associated with the topic, and infer the commonalities among them.

In Table 7, I list the poems the model predicts contain the highest amount of Topic 2 in them along with the probable proportion of the document that draws from Topic 2 (The amount of each basket the model predicts can be described as “apples,” for instance).

Table 11: Titles of the 15 poems most closely associated with Topic 2 and their corresponding topic distributions

<table>
<thead>
<tr>
<th>Topic 2</th>
<th>Title</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.535248643</td>
<td>When to the sessions of sweet silent thought (Sonnet 30)</td>
</tr>
<tr>
<td>0.533343438</td>
<td>By ways remote and distant waters sped (101)</td>
</tr>
<tr>
<td>0.517398877</td>
<td>A Psalm of Life</td>
</tr>
<tr>
<td>0.481152152</td>
<td>We Wear the Mask</td>
</tr>
<tr>
<td>0.477938906</td>
<td>The times are nightfall, look, their light grows less</td>
</tr>
<tr>
<td>0.472091675</td>
<td>The Slave's Complaint</td>
</tr>
<tr>
<td>0.451175606</td>
<td>The Guitar</td>
</tr>
<tr>
<td>0.447100571</td>
<td>Tears in Sleep</td>
</tr>
<tr>
<td>0.446314271</td>
<td>The Man with the Hoe</td>
</tr>
<tr>
<td>0.437962153</td>
<td>A Short Testament</td>
</tr>
<tr>
<td>0.433767746</td>
<td>Beyond the Years</td>
</tr>
<tr>
<td>0.433152279</td>
<td>Dead Fires</td>
</tr>
<tr>
<td>0.429638773</td>
<td>O Little Root of a Dream</td>
</tr>
</tbody>
</table>
Skimming the top fifteen poems associated with Topic 2 would confirm our assumption that the model has grouped together kinds of poetic language used to discuss death. Topic 2 is interesting for a number of reasons, not the least of which is that even though Paul Laurence Dunbar’s “We Wear the Mask” never once mentions the word “death,” the discourse Dunbar draws from to describe the erasure of identity and the shackles of racial injustice are identified by the model as drawing heavily from language associated with death, loss, and internal turmoil—language which “The Starry Night” indisputably also draws from. To say that Topic 2 is about “death, loss, and internal turmoil” is overly simplistic and does not reflect the wide ranging attitudes toward loss and death that are present throughout the poems associated with this topic; however, to say that Topic 2 draws from the language of elegy would be accurate. Identifying that Dunbar’s “We Wear the Mask” and “The Slave’s Complaint” draws from the discourses associated with elegy supports recent scholarship by Marcellus Blout in “Paul Lawrence Dunbar and the African American Elegy:”

I am using a set of terms that point to how I see Dunbar as initiating a tradition of African American elegies. I should underscore here that I am not arguing that the African American practice of the elegy is necessarily distinctive from other traditions of the elegy. But I want to suggest that such practice is continuous. Dunbar’s poems of the 1890s point us directly to more recent elegies written by African Americans in the latter part of the twentieth century. (241)

By grouping Dunbar’s poems in a topic of elegiac language, the topic model supports Blout’s claims that Dunbar’s poems participate in elegiac discourse as a means of identity
formation for African Americans at the turn of the twentieth century. What the topic model (and more likely the networked close readings that will be drawn from the topic model) might also help identify is whether or not other poems by contemporary African American poets similarly draw from Topic 2, further supporting Blout’s claim that Dunbar “initiates a tradition.” The promise for future study is that as the corpus of poetry in the “Revising Ekphrasis” dataset grows, more questions such as these could be fruitfully explored.

Just as semantically evident topics require interpretation, determining the coherence of a semantically opaque topic requires closer reading of the documents most closely associated with each topic in order to check whether or not the poems are drawing on a similar discourse, even if those same poems have different thematic concerns. While semantically evident topics gravitate toward recurring images, metaphors, and particular literary devices, semantically opaque topics often emphasize tone. Words like “death, life, heart, dead, long, world” out of context tell us nothing about an author’s attitude or thematic relationships between poems, but when a disciplinary expert scales down into close readings of the compressed language of the poems themselves, one finds that there are rich deposits of hermeneutic possibility available there.

Searching for thematic coherence in topics formed from poetic corpora would prove disappointing since such keyword distributions in a thematic light appear riddled with “intrusions.” However, by understanding topics as forms of discourse that must be accompanied by close readings of the poems associated with each topic, researchers can make use of a powerful tool with which to explore latent patterns in poetic texts. For poetry data in particular and literary texts in general, close reading and contextual
understanding must be brought to bear on the computer algorithm used for distant reading but it is worth pursuing because the potential for making discoveries and improving the range of questions we might be able to ask about poetic texts holds great promise. While this study is limited by its focus on ekphrastic poetry within one dataset, I hope that it is also suggestive of future research that helps develop best practices for measuring the accuracy and interpretability of topic models of humanities data because the methodology represents an important area for increasing the scope of humanities questions we can ask in the future. As such, the claims above are relevant for humanities scholars who wish to try distant reading approaches, but also for computer scientists and digital humanists developing those technologies and training future scholars.

Social Network and Scalable Readings

Knowing that topic models offer potentially rich opportunities for increasing the scope of the questions we can ask about literary tradition and poetic discourses by classifying hundreds to thousands of poems more quickly than human scholars could on their own and that LDA can generate useful connections between texts by detecting latent patterns of language, having an effective way to pan the critical lens in and out of topic models improves the scholar’s ability to make sense out of the vast amounts of data topic models create is critical. Furthermore, while bar graphs, scatter plots, and pie charts help visualize trends at either end of the spectrum—either in single or small sets of documents or vaguely across much larger sets of documents—they are less successful at helping readers move fluidly through the relationships created by the topic model. That “The Starry Night” draws from discourses of night and death could be discovered more easily through human close reading if we were only interested in the discourses of a single
poem; however, if we want to exploit the vast numbers of connections created between documents in a topic model, network visualizations are more promising because they have the potential to scale from distant, broadly-conceived connections down to more intimate clusters of connections. In other words, network visualizations allow us to see the way in which the discourses of “The Starry Night” are connected to the 4,499 other poems in the model and then zoom in more closely to connections between a few hundred poems, and then in even further to intimate connections between a 10-20 documents. In *The Dialogic Imagination: Four Essays*, Bakhtin makes the following assertion:

> The word in language is half someone else’s. It becomes “one’s own” only when the speaker populates it with his own intention, his own accent, when he appropriates the word, adapting it to his own semantic and expressive intention. Prior to this moment of appropriation, the word does not exist in a neutral and impersonal language (it is not, after all, out of a dictionary that the speaker gets his words!), but rather it exists in other people’s mouths, in other people’s contexts, serving other people’s intentions: it is from there that one must take the word, and make it one’s own. (293-4)

Ekphrasis, particularly in the twentieth-century, knowingly enters into a socially-charged network of artists, artworks, poems, and readers and, like the words Bakhtin describes, ekphrastic poems are doubly charged with the sense of representational “afterness.” So the network environment is a fitting medium for uncovering the way in which ekphrastic poems connect and respond to the discourses that surround them, which they appropriate, disrupt, or ignore.

In this second section, I create a topic model of ekphrastic poems and demonstrate how topics as forms of discourse create salient connections between hundreds of poems. With an awareness of the types of topics described in the previous section, I will present

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methods of visualizing the topic model results to uncover unexpected connections and prompt questions about the discourses of ekphrasis. Furthermore, I suggest using additional algorithms to cluster connections between documents and multiple topics, which increases the salience of the topic model’s results. Beginning with a subset of 276 ekphrastic poems from the “Revising Ekphrasis” dataset, I create a 15-topic model and visualize the relationships between topics and documents in three possible ways, considering what questions might be asked about the network with each separate rendering.116

The following graphs are produced with social network software called NodeXL, which is integrated into Microsoft Excel. NodeXL is the best available software to use for the visualizations because, like every other digital tool in this study, it is freely available to the public, has the lowest possible learning threshold for task it needs to perform, and it is robust enough to create network visualizations of topic models as well as any other software available at the time this study was performed. Using NodeXL’s suite of “clustering” algorithms, I am able to reorganize, synthesize, and manipulate thousands of relationships between topics and documents with relative ease. As a quick review, networks visualize relationships between nodes. In the case of the topic model, there are two possible types of nodes: documents and topics. Returning to the farmer’s market analogy from the beginning of the chapter, I can visualize edges (meaning connections) between the kinds of produce offered at the farmers market and the individual baskets using the proportion of each topic found in each document. For

116 The process by which poems were selected and described can be found in chapter 4.
example, the proportion of apples in each basket establishes the degree to which the
basket shares an edge with a type of produce. I could also use another calculation created
by the model that calculates each document’s degree of similarity to other documents.
Returning to the market example, baskets are compared to other baskets using the
relationship between the proportions of different kinds of produce in each individual
basket. A similar form of relationship is calculated between topics and other topics. For
example, the kinds of produce at the market share a relationship with one another based
on the amount of each kind of produce found in each individual basket.

Using the model’s calculations, I can visualize relationships between each node
(types of produce and baskets) with edges (the lines between nodes on the graph) that
represent the degree of relatedness between each node. This tends to produce very large
tables with a dense number of connections, but after exploring how the networks
represent the model data, the use of algorithms that cluster together multiple topics and
multiple documents based on similarities among them, proves to be the most powerful
potential for this form of organizing, navigating, and visualizing ekphrasis.

In the small dataset of 276 ekphrastic poems, the topic keys are mostly
semantically opaque. If we were to use the word intrusion threshold that Chang, et. al.
describe in “Reading the Tea Leaves,” we would, most likely throw this model out. The
topic keyword distributions (top 20 words in descending order of probability) displayed
in Table 8 would not likely stand out to most readers—even disciplinary experts—and
the addition of an “intruder” would not likely improve one’s ability to see the key words
as comprehensible. The topic keyword distribution in Table 8 is like similar tables found
during the stoplist tests in the previous chapter. On the far left under the label “Topic” is
a numbered list that acts like an empty container into which the LDA algorithm sorts words to create topics. The next column to the right labeled “Probability” represents the model’s prediction of the proportions of the entire corpus that likely draw their words from each topic. For instance, if Topic 0 were “squash” in the market example, then the model predicts that .02587 (or about 2.6%) of the entire selection of produce at the market is likely to be squash. The third column, “Keywords”, would include samples of squash from the entire selection at the farmer’s market from the most likely to the least likely to be found.

Table 12: Keyword Distribution for 15 Topic Model of 276 Ekphrastic Poems

<table>
<thead>
<tr>
<th>Topic</th>
<th>Probability</th>
<th>Keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.02587</td>
<td>orange dido tristan iseult linnet drop mark cousin roof fish union ysolt tintagel boston elizabeth crushing aquarium ladies free beating</td>
</tr>
<tr>
<td>1</td>
<td>0.03476</td>
<td>matter clay angel palm fold cup pots napkin soul folds form table point full place pieces lettuce hiding wet ugly</td>
</tr>
<tr>
<td>2</td>
<td>0.04023</td>
<td>wing person friends don girls human consciousness understand nature wait space film story david audience owl write reality art light</td>
</tr>
<tr>
<td>3</td>
<td>0.05145</td>
<td>thy thou thee er beauty art death picture grace hath sea eyes tis heaven spirit doth divine till hand love</td>
</tr>
<tr>
<td>4</td>
<td>0.04261</td>
<td>portrait monument foreman felt women monuments box press bacall detail young thick crimson instrument hotel compartment picked cornell europe lovers</td>
</tr>
<tr>
<td>5</td>
<td>0.0671</td>
<td>girl dance flags teacher dress icarus wall wood flag edge brueghel sun field round sing blue soil waving san market</td>
</tr>
<tr>
<td>6</td>
<td>0.06105</td>
<td>hill snow winter birds colors fire trees ice tall figures scene pack returning hounds brown evening dogs heel town jar</td>
</tr>
<tr>
<td>7</td>
<td>0.07064</td>
<td>surface body water bridge houses leaves model matisse hills pond photograph step silence woman artist flat leaning desire curve child</td>
</tr>
<tr>
<td>8</td>
<td>0.05386</td>
<td>world god death man lands light made thing back soul give face shape centuries flesh time set ancient terror rose</td>
</tr>
<tr>
<td>9</td>
<td>0.04185</td>
<td>train work left art vermeer horse don paint number good flood home stieglitz cane dragon burning church blood village fresh</td>
</tr>
<tr>
<td>10</td>
<td>0.02111</td>
<td>guitar blue things horizon final stone friend native patch tune mind sea music tom works manner poetry dream call oxidia</td>
</tr>
<tr>
<td>11</td>
<td>0.0396</td>
<td>coat back suddenly visible floats giving origin completed sensation floating tree open understand weave filled things cut shade fine garment</td>
</tr>
<tr>
<td>12</td>
<td>0.70035</td>
<td>light white man world time life long air face day blue sky water dark eyes hand dead body head great</td>
</tr>
<tr>
<td>13</td>
<td>0.04796</td>
<td>painted age hopper edward body background poster hungry bread ve ghost bed ashamed ten bricks doesn foreground hat silently gothic</td>
</tr>
<tr>
<td>14</td>
<td>0.02993</td>
<td>silver golden field country bound arms rise scratched thunder pleasant</td>
</tr>
</tbody>
</table>
Visualizing Topics as Discourse Networks

Once we have a sense that the keyword distributions in topics, we can begin visualizing the data from the model. The first network graph (Figure 40) displays affiliations between two groups: topics (the randomly generated number on the left) and individual documents in the collection. Because the graph contains two types of nodes (the points on the network diagram that represent documents and topics), the graph is called an affiliation network. We learn from affiliation networks that individual documents share some proportion of their language with other documents that also have edges to the same topic. Since there are 15 topics and 276 poems, there is a possibility of 4,140 possible edges (lines) between 391 nodes (276 poems x 15 topics). Though 4,000 is not too many to still be able create an understandable graph, removing those edges (lines) that are predicted to include less than 10% of the words from a topic would make the graph more readable because there would be slightly fewer edges to contend with; therefore the “baskets” (documents) drawing .1 (10%) or less from a “kind of produce” (topic) are removed from the graph. What remains, then is a network of individual poems (documents) that draw at least 10% of their words from the topics with which they share an edge (line). Therefore, if “Rükenfigur” by Susan Howe and “For the Union Dead” by Robert Lowell (in hot pink on the right side of the graph) are both predicted to draw more than 10% of their language from Topic 0, which they are, then they share an affiliation with one another through their mutual connection to Topic 0.
In terms of the graphic signification of the network, the nodes of the network are assigned a distinct color based on its affiliation with a topic. The labels for nodes representing poems include the first 15 characters of the poem’s title. The labels for the topics are just the topic number as it was assigned in the topic keyword distribution table above (Table 8). Furthermore, the edges between nodes vary in terms of thickness and color based on the proportion of the document that draws from the words in the corresponding topic. In other words, if the “Man with a Blue Guitar” draws 15% of its language from Topic 7, the edge that connects the node to the topic would be thin and dark blue. Conversely, if the node representing “Red Quiet” is predicted to draw 40% of its language from Topic 4, the edge connecting the two nodes would be a thicker line in lighter blue.\footnote{Admittedly, the use of thick, light lines for larger proportions and thin, dark lines for smaller proportions may seem confusing since we usually attribute thicker and darker lines with greater significance and thinner, lighter lines with less weighty signification; however, the purpose was to keep the graph readable. Thick dark lines would obscure the visibility of the smaller but significant relationships. Furthermore, using a variation in color improves the visibility of the graph over all, but adding the variable widths of the lines helps to some degree with those who are unable to see the change in color. There is, within the field of information visualization, a serious conversation about how to better represent large data—in ways that are as explicit and readable as possible, but that do not reduce the data so far in the process that the data loses its accuracy. Developers at the Social Media Research Foundation, the group responsible for improving and maintaining NodeXL, are striving to improve the suite of available tools to be able to create graphs that represent the largest amount of data with the least possible attrition. For more information, see www.socialmediaresearchfoundation.org.}

We know from Table 8 that the topic with the largest proportion across the whole collection is Topic 12. Predictably, then, Topic 12 can be located easily on the
When I first began to create the network graphs for this model, the labels for the documents were the document identifier numbers,¹¹⁸ and I noticed that all of the nodes with connections to Topic 3 (upper left hand corner in dark blue) in Figure 40 (Topic 3 is highlighted in teal in Figure 41) began with the same two letters—gs—meaning that they all came from John Hollander’s anthology of ekphrasis titled *The Gazer’s Spirit*. Though the topic label is small and compared to other topics in the network has fewer edges, the edges that connect to it are quite thick, indicating that a few poems in the collection draw

¹¹⁸ The random alpha-numeric identifying number assigned to each poem when the dataset was created, the process for assigning unique identification numbers to poems and documents is described in chapter 4.
quite heavily from the word distribution in Topic 3. The model, which does not possess foreknowledge about where the documents come from, detected latent patterns of discourse in *The Gazer’s Spirit*, and even after 5 re-runnings of the same model, one of which included 200 additional non-ekphrastic poems, the pattern proved consistent and reproducible to the point that I feel confident labeling the topic the Gazer’s Spirit Topic. The keyword distribution for the Gazer’s Spirit Topic reflects a combination of archaic discourse (thy, thee, thou) and the discourse of courtly love (er, beauty, grace, eyes, heaven, divine, hand, love). This makes sense in the context of existing knowledge about Hollander’s volume. The collection reads like a tribute to painting and the visual arts by poetry, and the language of desire is strong. If, as W.J.T. Mitchell and James A.W. Heffernan have claimed, the language of affection, love, and desire fuels the defining gendered stance between poetry and the visual arts, then it would also be reasonable to assume that the discourse of courtship and desire would appear more broadly throughout most of the documents. But it doesn’t. Every one of the 20 poems with a greater than 10% distribution of words from the Gazer’s Spirit Topic come from *The Gazer’s Spirit*, and interestingly only one of those was written by a woman. In fact, of all the poems likely to have a 10% or greater distribution of words from the Gazer’s Spirit Topic, only a few of the poems with a statistically significant portion of its language from Topic 3 are not also in *The Gazer’s Spirit*: “The Picture of Little T.C. in a Prospect of Flowers,” “The Art of Poetry [excerpt],” “Ozymandius,” and “Canto I.” Of those poems, none are by female poets.

<table>
<thead>
<tr>
<th>Table 13: 20 Poems predicted to draw 10% or more of its language from Topic 3 / The Gazer's Spirit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 20 Poems with Probability &gt; 10% of Topic 3</td>
</tr>
<tr>
<td>The Temeraire (Supposed to Have Been Suggested to an Englishman of the Old Order by Lisa Marie Antonille Rhody Chapter 5, Ekphrastic Revisions)</td>
</tr>
<tr>
<td>Description</td>
</tr>
<tr>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>the Flight of the Monitor and Merrimac</td>
</tr>
<tr>
<td>To my Worthy Friend Mr. Peter Lilly: on that Excellent Picture of His majesty, and the Duke of York, drawne by him at Hampton-Court</td>
</tr>
<tr>
<td>From The Testament of Beauty, Book III</td>
</tr>
<tr>
<td>For Spring By Sandro Botticelli (In the Academia of Florence)</td>
</tr>
<tr>
<td>To the Statue on the Capitol: Looking Eastward at Dawn</td>
</tr>
<tr>
<td>The Poem of Jacobus Sadoletus on the Statue of Laocoon</td>
</tr>
<tr>
<td>To the Fragment of a Statue of Hercules, Commonly Called the Torso</td>
</tr>
<tr>
<td>The Last of England</td>
</tr>
<tr>
<td>On the Group of the Three Angels Before the Tent of Abraham</td>
</tr>
<tr>
<td>Death's Valley</td>
</tr>
<tr>
<td>from the painting by George Inness</td>
</tr>
<tr>
<td>Elegiac Stanzas Suggested by a Picture of Peele Castle, in a Storm</td>
</tr>
<tr>
<td>Painted by Sir George Beaumont</td>
</tr>
<tr>
<td>On the Medusa of Leonardo da Vinci in the Florentine Gallery</td>
</tr>
<tr>
<td>The Mind of the Frontispiece to a Book</td>
</tr>
<tr>
<td>Venus de Milo</td>
</tr>
<tr>
<td>The City of Dreadful Night</td>
</tr>
<tr>
<td>Sonnet by Pietro Aretino</td>
</tr>
<tr>
<td>For &quot;Our Lady of the Rocks&quot;</td>
</tr>
<tr>
<td>Mona Lisa</td>
</tr>
<tr>
<td>Ode on a Grecian Urn</td>
</tr>
<tr>
<td>The National Painting</td>
</tr>
</tbody>
</table>

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A possible explanation for the clear association between the poems in the Gazer’s Spirit Topic might be that most of the poems the model predicts most closely associated with the discourse found there were published prior to 1900. Out of the top 20 poems drawing from the Gazer’s Spirit Topic only “from The Testament of Beauty, Book III” by Robert Bridges and “Mona Lisa” by Edith Wharton were published in the 20th century, begging the question: is the identification of the archaic discourse of courtly love merely a function of when the poems were written? At this point, careful attention should be paid to the outliers of the group. With regard to Wharton’s “Mona Lisa,” the poem is distinctive within The Gazer’s Spirit in large part because it never mentions the primary
subject of the painting except in its title. As Heffernan describes in his accompanying discussion of the poem:

> Wharton very cleverly avoids all of the celebrated questions in which the portrait comes officially wrapped (the sitter’s gaze, what it betokens, the nature of the smile…) by looking only at the magnificent landscape behind her, extending almost two thirds of the way down the panel, in a tone influenced partly by Rossetti, partly perhaps by George Meredith’s sonnets in *Modern Love.* (236)

Heffernan correctly identifies Wharton’s *tone* as akin to Dante Gabriel Rossetti’s, but not the manner in which she deploys that tone. Rossetti’s poems, much like his paintings, are forever driven back to the idealized physical countenance of the woman in the frame. Wharton purposefully looks around the woman in the portrait and describes the landscape using the archaic discourse of courtly love, and in doing so calls attention to the painter’s treatment of the sitter as one more object literally framed by a similarly romantic, idealized sensibility.

Reframing topics as forms of discourse rather than thematic groups is a critical feature of the combined use of topic modeling and network analysis as a methodology because it requires that we continually refocus the aperture of our critical view. Our search for relationships between poems and our search for distinctive features of ekphrasis as a genre within the network needs to consider not only what the poems associated with a topic have in common but also what they do not. Such an approach helps us avoid the easy resolution that would otherwise gloss over the distinction between Wharton’s poem and the others in the topic. More importantly, though, we would miss opportunities to ask more refined questions, such as: if Wharton’s companion poem to “Mona Lisa,” “La Vierge Au Donateur” had been included in the topic model, would it,
too, have been as closely associated with the same topic or another? In fact, Wharton’s poems come as a pair titled “Two Backgrounds,” and one might even be prompted to consider if reading them separately is an accurate way to read the poems to begin with, as one seems to depend so heavily on the other for counterbalance. Pairing the two poems and the work of art, Wharton clearly sees them as a conversation between two views and invites her readers to join in their conversation—precisely the kind of reading that a networked critical approach, such as this one, is designed to do.

Hollander, one might argue, purposefully selected Wharton’s “Mona Lisa” because it disrupted the archaic courtly love discourse so pervasive in the volume’s early poems and points to the fact that there are critical antecedents to the networked reading I’m suggesting here. Anthologies often select an outlier or two to complicate potentially reductive assumptions about the collection as a whole; however, what Hollander’s critical anthology cannot accomplish as easily is to essentially pan back out of a collection of 30 to 40 poems to see those collectively within a the larger context of several hundred poems, find another related discourse, and then narrow the lens again to perform readings from a middle or close distance.

**Locating Similarities between Discourses**

Switching away, momentarily, from highly detailed network between individual documents and topics and backing out even further from the data, the next graph considers relationships between the 15 topics in the model. Looking at topic to topic edges (lines between topics) is one way to see the degree of similarity between them. Returning once again to the anecdote of the farmer’s market begun at the start of the chapter, you predicted the kinds of produce (topics) available at the market based on the
individual units of produce found in each basket. For example, the “apples” topic is actually a representation of thousands of examples of round, red or green, glossy skinned fruit, while the “pears” kind is really a representation of all the bottom-heavy, smooth-ish, green-ish fruit in each basket—both types of fruit. Topic to topic graphs, essentially, recognize that based on the samplings of “apples” and “pears,” those kinds of produce are more similar to one another than either of them are to “cucumbers.”

Similarly, visualizing the topic to topic similarities and differences in the network of ekphrastic poems synthesizes within a macroscopic view the relationships between discourses the model identifies. In the graph below, the degree of similarity between topics (in other words the likelihood that apples are like pears) is represented by the thickness and color of ties or edges between them (in other words, not based on the topics’ spatial orientation). Topics that share thicker, brighter red edges are more similar to each another than topics that share thinner, darker green edges.

Viewing the network this way is important because it helps us ask another type of question about the poems. We can consider how similar the model predicts the forms of discourse to be. For example, the model predicted that Topic 12 can be found in at least 70% of the ekphrastic dataset. That means that most of the collection draws from the discourse identified by the LDA as belonging to Topic 12; however, Topic 12 does not share a strong similarity with many of the other topics in the model. We know this because in the topic to topic graph in Figure 42, the edges connecting Topic 12 and most other topics are thin and green. The sole exception is the edge between Topic 12 and Topic 8, indicating that the language between those two topics share similarities, but that

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119 See the probability next to number 12 in Table 8.
there is a clear division between them and the distribution of language found in the rest of the model. Like the baskets from the farmer’s market that are composed of combinations of produce types, poems appropriate various forms of discourse, and so guided by the connections in the topic to topic graph, we can begin to ask questions about how we might use our knowledge about the similarities between topics to help us read laterally within the network. In other words, if we know that most poems contain some of Topic 12, how does the intervention of other, less prominent topics in the network affect the way we read the discourse identified in Topic 12?

Figure 42: Topic to Topic Network in the 15 Topic Model of 247 Ekphrastic Poems

Another possible approach to the topic to topic network is to continue to follow the Gazer’s Spirit Topic to see what other forms of discourse the model predicts are
similar to it. In Figure 43, Topic 3 is highlighted and reveals that the Gazer’s Spirit Topic is not as similar to other topics as most of the other topics (save 8 and 12). It would be reasonable to assume that the difference between the Gazer’s Spirit Topic and the others is a matter of the prominence of archaic discourse in The Gazer’s Spirit as compared with other poems in the collection that are more contemporary; however, the archaic discourse in the Gazer’s Spirit is also caught up in the discourse of courtly love. The topic to topic graph serves as a reading map, helping us chart the places in the ekphrastic collection to look for whether or not the distinctiveness of the Gazer’s Spirit is more a function of the archaic language or the language of desire.
Searching through the keyword distributions of the topics other than 3, 8, and 12 that have strong similarities to each other reveals that the only other topic to include in its top 20 key words that connote affection or desire is Topic 4. Returning to the topic keyword distribution in Table 8, the next most likely topic to include the word “love” in the first 20 words is Topic 4, which includes the following terms: portrait, monument, foreman, felt, woman, monuments, box, press, bacall, detail, young, thick, crimson, instrument, hotel, compartment, picked, cornell, Europe, lovers. As the topic to topic model predicts, the keyword distribution for the Gazer’s Spirit Topic is quite different.
from the keyword distribution in Topic 4. First, the keywords in Topic 4 demonstrate a more contemporary diction than does the Gazer’s Spirit Topic, but the difference is greater than that. Topic 4 includes names of specific artists (Cornell, Bacall), and the language of visual art is more specific (“portrait” in 4 rather than “picture” in 3). The sense of values and hierarchy is also more prominent in the Gazer’s Spirit Topic than in Topic 4. For example, topic 3 includes value-laden terms such as beauty, grace, divine, and heaven; whereas, Topic 4 focuses more on tangible objects: monument, box, compartment, foreman. Recalling that Wharton’s “Mona Lisa” in the Gazer’s Spirit Topic addresses one of the most recognizable portraits in Western art without ever describing its sitter, Topic 4 seems like an interesting place to begin comparing the two topics.

Returning once more to the network of documents and topics in Figure 44, we can see by selecting Topic 4 and highlighting all of its edges in orange, few poems associated with Topic 4 also share edges (connections to) The Gazer’s Spirit Topic (still in the top left-hand corner). Following each of the Topic 4 edges, what also becomes clear is that the poems in this neighborhood are also drawn toward other topics. The change in node color (most visible along the longer edges that are highlighted) demonstrates that the topic is also strongly associated with other topics—something not characteristic of the poems from the Gazer’ Spirit Topic.
Narrowing our focus even further to those 20 poems that draw most heavily from Topic 4 (Table 7) and comparing those to the 20 poems that draw most heavily from Topic 3 (Table 6), the most striking difference between the lists of poems and poets is that there is a much larger representation of poems by women. Even more striking is the number of poems that focus on portraits and self-portraiture. Linda Hull’s “‘Utopia Parkway’ after Joseph Cornell’s Penny Arcade Portrait of Lauren Bacall, 1945-6” by Joseph Cornell” combines personal memory and performance with Cornell’s homage to a 20-year old actress; meanwhile, Evie Shockley invokes the conventions of classical self-portraiture with contemporary substitutions for traditional iconography. Mary Rose
O’Reilley draws from the artist’s biography in “Portrait of Madame Monet on Her Deathbed” with an epigraph in which Monet confesses he could not stop painting his dying wife’s face, even though as, O’Reilley notes somewhat ironically, most of Monet’s portraits of his wife had become forms of her erasure in favor of the artist’s attention to light. Not every poem, though, is a portrait. An example of notional ekphrasis, “Internal Monument,” G. C. Waldrup’s prose poem, narrates the story of a man whose search for permanence and recognition become so burdensome that it leads to his early demise. As the monuments constructed inside the man become externalized after his death, the objects of memorial replace and subsequently erase the memory of the man who paid for their construction in the first place. With so many poems in Topic 4 considering portraits of one kind or another, Jorie Graham’s “Drawing Wildflowers” from *Hybrids of Plants and Ghosts* appears to be an outlier, as it does not represent a human figure at all, except that the work of art, her process of drawing wildflowers, makes and unmakes, draws and erases as the pencil and paper make their “gray war” together: “I can make it carry my fatigue, / or make it dying, the drawing becoming / a drawing of air making flowerlike wrinkles of the afternoon…” (ll 14-16). Similar to many of the portraits in Topic 4, Graham’s wildflowers are as much a manifestation of herself as they are representations of an external, natural object, an impulse considered self-consciously by each of the ekphrases on portraits in this topic.

**Table 14: Top 20 Poems Most Closely Associated with Topic 4**

<table>
<thead>
<tr>
<th>Poems with proportion &gt; 10% of Topic 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;Utopia Parkway&quot; after Joseph Cornell's Penny Arcade Portrait of Lauren Bacall, 1945 – 46 by Linda Hull</td>
</tr>
<tr>
<td>Canvas and Mirror by Evie Shockley</td>
</tr>
<tr>
<td>Portrait of Madame Monet on Her Deathbed by Mary Rose O’Reilley</td>
</tr>
<tr>
<td>Internal Monument by G. C. Waldrup</td>
</tr>
</tbody>
</table>
The Uses of Distortion by Caroline Crumpacker
Joseph Cornell, with Box by Michael Dumanis
Drawing Wildflowers by Jorie Graham
The Eye Like a Strange Balloon Mounts Toward Infinity by Mary Jo Bang
Visiting the Wise Men in Cologne by J.P. White
Rhyme by Robert Pinksy
The Street by Stephen Dobyns
The Portrait by Stanley Kunitz
"Picture of a 23-Year-Old Painted by His Friend of the Same Age, an Amateur" by C.P. Cavafy
Portrait in Georgia by Jean Toomer
For the Poem Paterson [1. Detail] William Carlos Williams
The Dance by William Carlos Williams
Late Self-Portrait by Rembrandt by Jane Hirshfield
Sea Life in St. Mark's Square by Mary O'Donnell
Washington's Monument, February, 1885 by Walt Whitman
Still Life by Jorie Graham
Still Life by Tony Hoagland
The Family Photograph by Vona Groarke

Reading the “unlike” discourses of the Gazer’s Spirit Topic and Topic 4 presents rich opportunities to discuss the plurality of attitudes and approaches women have brought to ekphrasis. The abstractions, erasures, and the language of making or being unmade in the portrait poems in Topic 4 share thematic similarities with Wharton’s “Mona Lisa,” whose famous countenance is never mentioned throughout Wharton’s poem except in the title; however, the means by which Wharton generates the poem, using the archaic discourse of courtly love, is distinctly different from the poems in Topic 4. In Topic 4 speakers self-consciously insert themselves into the display Wharton’s discourse adopts the voice of the detached observer to point to the painter’s inescapable presence in “Mona Lisa.” The combination of topic modeling and network analysis in this case provides a rich context of other poetic discourses that shed light on the subtle
choices and distinctions between the poems that captures the polyvocality of women’s ekphrasis. Even with a limited set of 276 poems, topic modeling has distinguished between two kinds of discourse used by female poets to comment upon portraiture.

Perhaps Wharton’s use of the archaic discourse of courtly love, as I mentioned earlier, within a context of other poems that similarly draw from such discourse to engage with visual images may seem like an opportunity already afforded to the reader of Hollander’s *The Gazer’s Spirit*; yet, what distinguishes the social network-situated readings that I’m suggesting here is the ability to consider the poem’s deliberate use of that discourse in a way that it can also be compared to the 20 other poems that draw from a discourse of performativity and erasure, such as those in Topic 4. Moreover, the nature of the network encourages the fluid movement between topics and invites comparisons and connections. Networked reading help us better see how the discourses women use in ekphrasis on portraiture draw purposefully from other kinds of discourses, accessing what we have known but that to this point has been difficult to articulate a methodology for—that the tradition of women writing ekphrasis is multifaceted, active, and draws from a wide range of possible discourses.

*Familiar Words in Alien Contexts*

The third and final possible entry point to viewing the ekphrastic network produced by the topic model is through document to document relationships. By approaching the network this way, we juxtapose the similarities between individual poem-level discourses and can ask detailed questions about how individual poems create and are created by an ekphrastic tradition. Returning one final time to the farmer’s market anecdote, comparing documents to other documents is like comparing each
individual neighbor’s basket to every other neighbor’s basket one at a time. In other words, LDA examines the content of one basket and calculates the degree of similarity between that basket and one other, a process that the model then repeats until every basket has been compared to every other basket. In the case of the ekphrastic dataset where there are 276 possible poems (“baskets”) each poem’s distribution of words (like the variety of produce in the “basket”), would be compared to each of the other individual poems’ distribution of words (variety of produce in each individual “basket”); thus creating 75,900 possible relationships between individual poems. To make as many comparisons through human reading would be impossible in the span of a single academic career; contrastingly, the LDA algorithm can complete this type of comparison in eight to ten minutes, depending on the capacity of the computer running the software. Granted, the comparisons that the topic model produces are limited—stoplist words have been removed, the LDA makes its predictions based on word co-occurrences rather than semantic context, and the results need to be accompanied with close readings to determine how “actionable” and “coherent” the topics produced by the model truly are. But as we learn how to read the LDA network with an awareness of the questions we can ask and the limitations that do exist, what we find is that the pairing of topic modeling and network analysis present a powerful tool for expanding the scale of our consideration of ekphrasis from 50 poems, as in the case of The Gazer’s Spirit, to 276 ekphrastic poems. The network also increases the dimensions of that comparison such that we can consider three possible types of relationship between the poems.

120 If there are 276 poems in the dataset and we compare them individually with the 275 other poems in the dataset, we arrive at 75,900 by multiplying 276 by 275.
The difference between looking at so many relationships within a relatively small number of documents, is that there are increasing numbers of ekphrastic poems that could be included in the model in future iterations of the project, is that 75,900 edges (lines on the graph connecting two poems or nodes) can be visually confusing. To put so many connections into the limited field of the page or screen is a challenge shared with many current visualization projects that struggle to represent large amounts of data and not a challenge easily overcome within the scope of this particular project; however, by keeping the dataset relatively small and by employing an additional algorithm from social networking, the following graphs attempt to find a middle-ground solution that, as technologies of visualizing large data improve, will likewise be refined. In the following graph, the document to document relationships between 276 poems are displayed in 14 “group” grid areas. The 14 groups do not reflect whether or not poems share the same topics as other poems in the way that the first network graph in the chapter did. Instead, I have used an algorithm from NodeXL which aggregates similarities that the topic model predicts to exist between individual documents and then creates “groups” of nodes (the representation of the poem in the graph, in this case a colored dot) based on how similar they are. Where documents are predicted to include higher degrees of similarity (i.e. the variety of produce in one basket is similar to the variety of produce in another basket) the nodes representing those poems are located spatially within the same grid of the graph. Furthermore, in the graph in Figure 45, darker and thicker blue lines denote stronger similarities between documents, while thinner, lighter blue lines designate documents with less similarity. Each group is characterized by its own color, which can be seen in the nodes and labels for each poem in each group. For example, all of the nodes and
labels for poems in Group 5 are red. Finally, in order to improve the visual
comprehensibility of the graph in this first instance, the labels for each node (representing
a poem) uses the poem’s unique identifying number, rather than the title of the poem.

Figure 45: Document to Document (Poem to Poem) Similarities Between 276 Ekphrastic Poems

Essentially, the document to document comparisons generated through the topic
model and then grouped together using NodeXL’s clustering algorithm creates
partitioned fields within the network grid area specific to each “group” of documents.
Although the document to document comparison the topic model makes is based on the
language from each individual poem and not on the topic assignments for that poem, the
likelihood that similar topics would also be found between the two documents that are
most similar is relatively high. When NodeXL uses the clustering algorithm to organize
the documents spatially, the groups in each grid area tend to draw from one to three of the
same topics. For example, the poems in Group 6, tend to draw from Topics 2 and 12.
The poems closer to the center of the cluster draw from a higher the proportion of Topic
2 than 12, and as the nodes move further away from the center, the proportion of Topic 2 from which the poems are predicted to draw from diminishes. Poems still included in Group 6 but further to the outskirts may also include distributions of other topics, such as Topic 5. By grouping poems in terms of their individual relationships to other poems across the network, we discover a multi-dimensional way to explore documents as combinations of discourses. Whereas the topic-to-document graph in Figure 40 focused on single discourses, groups of document-to-document relationships allow us to see the multifaceted ways in which documents combine those discourses and to contextualize individual poems within a dialogic of other poems that similarly draw from the same or similar topics but that may not be assigned to the same topics.

There are many possible directions that reading a graph with as much data as Figure 45 can take. Rather than trying to present them all here, I offer a few possibilities as provocations for future research. As our networked reading began by focusing on Edith Wharton’s “Mona Lisa,” it makes sense to follow the poem through the network. Predictably, many of the poems in Group 3, where “Mona Lisa” is located, are the same poems that draw from Topic 3 and Topic 12. However, there is one distinct edge between “Mona Lisa” and a poem clustered with Group 1, which happens to be John Stone’s “Three for the Mona Lisa.” Stone’s poem, firmly fixated on the portrait’s sitter, is sparse—60 words in all, divided into 3 sections. Of the 60 words in the poem, only 17 words would have remained after the stop words were removed during the preprocessing of the dataset; two of those from the title. It is fairly safe to say that what connects these poems...

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121 Recall that topic 12 is expected to be found in 70% of the ekphrastic poems in the dataset. Most of the poems include combinations of Topic 12 with varying proportions of other topics. In Group 3, those topics are most frequently 12 and 4.
two poems has little more to do with anything besides the fact that they mention the same portrait by name. That might not be enough to be a “discourse,”—except that within ekphrasis referring to a visual work by name establishes the immediacy of one’s conversation with it. Though there is little else between Wharton and Stone’s poems, Wharton’s use of the portrait’s title as both a direct invocation of the readers’ awareness of the famous smile and a purposeful avoidance of it participates in a conversation among the community of poems that invite readers to draw on their existing knowledge of the painting, a community of poems that John Stone’s joins many years later. Were there to be more poems added to the dataset in which poets purposefully use the title “Mona Lisa” somewhere within the poem, they would continue to build a dialectical network of ekphrases in which multiple discourses respond to the same work of art. True, critical work about the poetic responses to single works (e.g. *Hunters in the Snow* or *Landscape with the Fall of Icarus*) are numerous; however, a networked approach increases the dimension of such a study by allowing literary scholars to place individual responses to a single artwork within diverse discourse contexts. Wharton’s not only responds to the individual painting, but to an artistic tradition of representation that cannot be untethered from the same archaic diction that populates the other poems in the Gazer’s Spirit Topic. Approaching ekphrastic poems this way is made even more significant as it reinserts ekphrastic work by women inextricably into the tradition of ekphrasis. Whereas previous studies of ekphrasis could, because of the reasonable limitations of human reading and print availability, have missed examples of ekphrasis by women, a computationally-enabled and networked reading strategy insists that ekphrasis by women is not an
extricable, partitioned part of the ekphrastic tradition, but deeply-connected and influential.

Figure 46: Grouped Document to Document Relationships of 276 Ekphrastic poems, “Mona Lisa” by Edith Wharton Highlighted in Red.

Finally, in considerations of ekphrasis by women, poems about domestic objects of display has most often been either excluded or ignored. Indeed, Loizeaux suggests at the conclusion of her consideration of Marianne Moore and Adrienne Rich’s divergent forms of “feminist ekphrasis:”

It might open to view the home as an ekphrastic arena, as influential in shaping the genre as has been the art museum for the past 200 years. (The home was, after all, where art was displayed before the founding of public art museums in the eighteenth century. (108)
Contemporary women poets attuned to the domestic influence on the tradition of display, arrangement, and craft have continued to turn to household art—bowls, quilts, tapestry, needlepoint, and tea settings, for example. While creating the metadata for the collection, I specifically considered the feminine, domestic tradition of ekphrasis as an integral part of it, and poems that consider household objects, such as Rachel Contreni Flynn’s “Yellow Bowl.” Other considerations of ekphrasis might not have included Flynn’s poem as an example. The subject of a twelve line poem divided into four three-line stanzas, the yellow bowl in question rests on a table in the middle of a contemporary kitchen: “the yellow bowl on the table / rests with the sweet heft / of fruit…” (6-7).

Placed at the exact middle of the poem and the room, the bowl shapes the speaker’s perception of herself and her space as arrangements of containers and spaces for nurturing. The speaker, contained by the kitchen, cradles and sways a child in her arms, her own manifestation of the yellow bowl. The arrangement of the space improves the speaker’s capacity for affection because as it staves off the unspoken, but seemingly threatening sense of isolation (“and if I am singing / then loneliness has lost its shape, / then this quiet is only quiet.”)(ll 11-2). Flynn’s poem draws from the recognized ekphrastic tradition of Wallace Stevens’ “A Jar in Tennessee” but also the lesser considered precedents of Lydia Sigorney’s “To a Shred of Linen” and Johanna Baillie’s “Lines to a Teapot.” As of yet, little has been done to consider in greater detail the ways in which early ekphrastic poetry on household objects that might be considered more “craft” than fine art have influenced our ekphrastic heritage; however, the network graph of Flynn’s “Yellow Bowl” suggests that the broad reach of many of its edges in the document to document network in Figure 47 shows how comfortably the poem fits into
the ekphrastic tradition. Entering the ekphrastic network from the perspective of a single poem takes seriously our assumption that ekphrastic poems enter into a rich, historical, social, and ethical conversation with other poets, artists, kinds of art, poems, traditions, and readers.

![Document to Document Graph of Relationships Between 476 Ekphrastic Poems - "Yellow Bowl" Highlighted in Red](image)

**Figure 47: Document to Document Graph of Relationships Between 476 Ekphrastic Poems - "Yellow Bowl" Highlighted in Red**

**Conclusion**

Locating individual ekphrastic poems within the context of ongoing ekphrastic discourses, as I do with networked topic models of ekphrastic poems, foregrounds our understanding of ekphrasis as an ongoing dialectic of multiple, divergent conversations. By understanding topics as forms of discourse, we avoid the mistake of assuming that topics represent a stable idea or object. Topics are produced by the range of available
poetic works in a corpus. As the number of poems and range of poetic types in the modeled corpora grow, the topic output of the model will also reflect those changes, manifesting the dynamic and plastic nature of both discourses and LDA models. Because topic models are so responsive to changes in the composition of the dataset, network analysis is a fitting way in which to visualize and to “read” those discourses. Whereas previous theories of ekphrasis often perpetuate a static or limited understanding of ekphrasis (as a formal principle of all poetry akin to Murray Kreiger, as a manner of pictorialism, as semiotic translation, as a form of ideological narratives) the advantage to understanding ekphrasis as a dialogic engagement with multiple discourses and forms of meaning is that it better accounts for the inevitable changes and future developments of the genre without limiting it to a stable ideological construct in which the genre is considered as acting out moral anxieties about otherness. Therefore, LDA and network analysis are rich methodological approaches to the study of ekphrasis. While this chapter only hints provocatively toward possible future inquiry, the promise of the methodology is that it responds to the dynamic and responsive ekphrastic situation as a poet’s entrance into an ongoing, network of social, visual, and verbal conversations.

This exploratory approach to large numbers of texts, and it is possible that the researcher who sifts through and closely reads poems individually decides that some of the results are not significant and that the model may need modifications. For instance, 276 poems forms a small dataset to work with. Increasing the total numbers of ekphrastic poems in the dataset would improve the model’s topic distribution. Furthermore, the ability to differentiate poems within the dataset by the date of publication may give increased weight to poems that do not have distinguishing archaic terms such as “thee”
and “thou.” We might also discover that results from a few poems that are longer than the rest pull the topic distributions in ways that skew the representation of the remaining texts. In this instance, better “chunking” or division of documents would improve the overall shape and suggestiveness of the models produced with LDA and, correspondingly, the network graphs which represent those results.

Current development in topic modeling looks quite promising for figurative language datasets. Interactive topic modeling programs allow users to interrupt, modify, and rebuild topic models without having to start at the beginning each time. While some early results of less successful models may be frustrating, interactive topic model programs currently in development might improve our ability to create useful models. With interactive topic models, human input during the running of the topic model that allows for corrections while generating the model may help to improve future outcomes.

However, even if more, better data could alter the kinds of hypotheses we form about the results or more interactive topic modeling programs could help us to correct for ambiguities, the methodology itself remains highly promising and has the potential to lead to close readings that pair texts in fresh and innovative ways. In this regard, Moretti makes his most powerful point. What LDA models, graphs, trees, and tables do is increase the researcher and literary scholar’s scope. Rather than suffer the limitations of human memory, this form of computational analysis encourages connected discovery that extends disciplinary expertise in useful ways—much the way Vannavar Bush imagined the Memex would. In other words, the expertise and deep knowledge of the human scholar is prompted by the voluminous capacity of “reading machines,” as Stephen
Ramsay calls them, and visualizations to expand and to test the literary scholar’s assumptions or to attend to important nuances in existing knowledge.

I’m unable to explore here all of the possible questions we might be prompted to ask by the combination of topic modeling and network analysis to render networked, dynamic readings of ekphrasis. The purpose of this chapter has been to explore what opportunities might be presented and what questions asked by combining the computational strengths of algorithms such as LDA and the visualizations produced through network graphs. To read ekphrasis as/in a dynamic network allows the literary scholar to draw from an unprecedented scope of ekphrastic examples and to make critical interventions at multiple reading “distances.” By reading and navigating collections of ekphrasis this way, we are better able to recast its canon, its tradition, and our understanding of how the genre operates.