Metaphorical Visualization: Mapping Data to Familiar Concepts

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ABSTRACT

We present a new approach to visualizing data that is well-suited for personal and casual applications. The idea is to map the data to another dataset that is already familiar to the user, and then rely on their existing knowledge to illustrate relationships in the data. We construct the map by preserving pairwise distances or by maintaining relative values of specific data attributes. This *metaphorical* mapping is very flexible and allows us to adapt the visualization to its application and target audience. We present several examples where we map data to different domains and representations. This includes mapping data to cat images, encoding research interests with neural style transfer and representing movies as stars in the night sky. Overall, we find that although metaphors are not as accurate as the traditional techniques, they can help design engaging and personalized visualizations.

CCS CONCEPTS

• **Human-centered computing → Visualization techniques**; *Visualization theory, concepts and paradigms*; • **Computing methodologies** → *Machine learning*.

KEYWORDS

Metaphor, Word embedding, Image embedding

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1 INTRODUCTION

The traditional view of data visualization presents the user as a trained specialist performing data analysis as part of their occupation. In this context, a visualization application is primarily evaluated by its efficiency, accuracy and scalability. However, there are many visualization "edge cases" that do not fit this description [40]. For example, ambient visualization might trade accuracy and richness of encoded information for aesthetic qualities. And in science communication, the engagement of the audience can be one of the most essential factors [6, 48].

Similar scenarios are described under the umbrella of Personal Visualization [22], referring to both visualization of personal egocentric data and data analysis in the personal context. Here, a user might have very different goals, background and expectations, when compared to a professional. Over the years, there were a number of applications that explored these research directions and were used by a much wider public for their personal goals and data. For example, Wordle was used to create more than 600,000 word clouds [46]. LastHistory allowed thousands of users to visualize their listening history [3]. These and similar PersonalVis applications create an additional set of challenges that may rival or even eclipse the more classical evaluation criteria. Personal visualization should be accessible and address the personal goals of the user. But above all, in our opinion, it should be engaging and fun, as it encourages people to experiment with visualization and stay long enough to appreciate its rewards and more "serious" methods.

In this paper, we invite the reader to consider data visualization through the lens of metaphors, as we believe this perspective can help us create more accessible and engaging visualizations. Cognitive linguists argue that metaphors are not only a poetic device, but are central to our language and cognition [30]. Every day we implicitly use *conceptual metaphors* like "time is a moving object" (time "flies", the time "will come", etc.) or "theories are buildings" (they are constructed, have a foundation, etc.) to help us structure complex ideas. Considering how pervasive metaphors are in our thinking, it is not surprising to find us using metaphors to understand our data. Visualization relies on many similar conceptual metaphors (e.g. "green is good", "up is more"), but is also itself a form of metaphor that helps us interpret abstract data entities in terms of visual experiences. Mapping prices and countries to positions and colors is a metaphor that focuses on directly representing some aspects of the data (often numerical or categorical) as visual primitives.

What we propose in this paper is to extend the visualization metaphors beyond the visual. We can devise new ways of representing data by mapping it to concepts that are tacitly understood by humans. So, if we have data from two domains, one of which is familiar to the user, we can map the entities (data points) of the

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unknown domain to the entities of the known one. For example, by preserving pairwise similarity, we can map data to words and learn that points X, Y and Z relate to each other like "dog", "house" and "chimney". Although the interpretation of relationships between words is somewhat ambiguous, we can leverage our knowledge of word similarity to explore the data.

Conveying information in the form of metaphors is innately familiar to humans and requires less expertise from the user, especially compared to the "expert" alternatives, such as glyphs, parallel coordinate plots and dimensionality reduction algorithms. Additionally, we can tailor the metaphor to the application context: if we are creating an infographic for an astronomy magazine, we could map our data to stars in the night sky, but we might use popular movies for the general public. Most importantly, it becomes possible to generate fun and vivid associations and provide an engaging way of communicating data that is suitable for more casual applications.

We call this approach *Metaphorical Visualization*. In what follows, we will present diverse examples of metaphorical mappings, discuss their strengths and weaknesses and how they fit together under the umbrella of metaphors.

2 METAPHORICAL VISUALIZATION

The main idea of our approach is to leverage the user's knowledge of one domain to learn more about another. Practically, this means that there is a dataset of interest and some data about another domain that is familiar to the user. We call the former *the data space* and the latter *the concept space*, where both are a discrete set of entities (data points or concepts). Our goal is to find a mapping of data onto concepts such that the relationships in the data space are preserved in the concept space. For example, we can express similarities between researchers (data) by mapping them to English nouns (concepts), such that related researchers are assigned to related words.

The key consideration in creating a metaphor is defining the relationships that should be preserved by the mapping. Depending on the structure of the data and the application, there could be several alternatives. We distinguish between distance-based, attribute-based, topology-based and hybrid methods of constructing the metaphor.

Distance-based mapping. In this type of mapping, we have a distance function in both spaces, which quantifies the pairwise similarity of points. We then compute a discrete assignment that aims to preserve distances, i.e., the distance between points in the data space should be as close as possible to the distances between their assigned concepts. With this mapping, the users can explore the pairwise similarities in the data by comparing the concepts, but also form groups of related data-concept pairs. The biggest advantage of this approach is its flexibility: we can use almost anything as the concept space, as long as it has a distance function. The richer the relationships captured by the distances, the more nuanced of a metaphor we can construct. We find this method to be most useful when we can apply machine learning models to construct distance functions for both spaces, allowing us to use complex entities, such as people, words, images, etc. In Sec. 5, we show how we can construct a distance function for researchers and then represent them with English nouns or with cat images, mapping between different ML embedding spaces.

Attribute-based mapping. This type of metaphor is applicable for tabular data with directly interpretable attributes. We can specify which data and concept attributes should have similar values. Unlike the distance-based mapping, we no longer define similarity among data/concept points, but instead specify similarity of data to concepts, i.e. across spaces. Therefore, the attribute-based method should be used when we have distinct features that can be conceptually related to each other. This gives us direct control over the metaphor and makes it easier to interpret, although it can lose some subtleties of a distance-based mapping. In Sec. 6, we use this approach to map between books, movies and games, such that their rating and popularity have analogous values, finding the "Twilight" among the games and the "Shawshank Redemption" of books.

Topological mapping can be pursued when the exact distances are not important or not available. For instance, when constructing metaphors for network data or hierarchies, the relations in the data are modeled as a graph. Here, we need to build a mapping that preserves topology, e.g., adjacency for generic graphs or descendancy for trees. Interestingly, dimensionality reduction techniques like t-SNE or UMAP can also be considered a topological metaphor since they only preserve the local neighborhood and not the exact distances. An example of a topological mapping could be found in the supplemental materials (see Sec. 4), where we map a taxonomy of sciences onto a taxonomy of industries while preserving the parent-descendant relations.

The three conceptual approaches above are distinct from each other but are not mutually exclusive. They can be combined to produce *hybrid* mappings. This might be desirable, for example, when we want to control an aspect of a distance-based metaphor by explicitly connecting some of the data and concept attributes. For example, in Sec. 7, we use both distances and attributes to produce the mapping of movies to stars in the night sky. There, we match the movie rating to stars' brightness (attribute mapping), while also ensuring that similar movies are represented by nearby stars (distance mapping).

Overall, there are could be many ways of defining and computing a metaphorical mapping, but they all share the overarching idea of representing data from one domain using another. In this work, we chose to implement the idea by computing discrete assignments between the two spaces, often using machine learning models to measure similarity. In what follows, we present many concrete examples of metaphorical visualization and use them to demonstrate its advantages, discuss its limitations and outline important design considerations.

3 RELATED WORK

Metaphors for interaction and visualization. Metaphors have a long history in HCI, appearing as early as the first personal computers, where they were required for describing novel objects and interactions [19, 41]. Finding effective interaction metaphors is also an important challenge for VR/AR applications [25, 37]. For example, designing an input mapping for 3D object manipulation often involves physical object metaphors: a balloon-on-a-string [5], corkscrew [11], handlebar [45], crank handle [9], and many others. Metaphors are also prominent in visualization where they are used for interaction, but also to construct visual representations. For instance, Havre et al. [20] proposed a river metaphor to represent themes in document collections. And a city metaphor can be used to represent software architecture [24]. Overall, choosing an appropriate metaphor can have a noticeable impact on user performance [49]. In this paper, we extend the usage of metaphors for visualization from conceptual metaphors that structure the representation to computing mappings between concrete entities. So, for example, where ThemeRiver [20] would present topics as lines resembling rivers, we would map the topics to real rivers, using their properties to represent the data.

Metaphors can find applications in communicating information to wider audiences, where connecting to people and building their interest can be more important than conveying the raw facts. For example, in cinematic SciVis [7], metaphors are vital in conveying the subject to the audience. They are also prominent in computer science education [43], helping introduce abstract concepts. Finally, metaphors play an important role in creating infographics, where making the visualization memorable [8] and aesthetically pleasing [18] are important considerations.

Image and style embeddings. Several of our implementations rely on machine learning models. Specifically, on image embeddings, which are most often constructed in the context of generative models and self-supervised pre-training for computer vision tasks. For example, Dosovitskiy et al. [15] applied random transformation to learn a robust image embedding space, and Doersch et al. [13] predicted positions of image patches to learn image features (see [14] and [26] for an overview). There have been a few works aiming to construct style embeddings or learn style similarity. Lun et al. [34] used geometric similarities and supervised data to construct a model of style similarity, and Bell and Bala [4] trained a siamese network to construct a style embedding to search for products with similar design. In this paper, we use the SimCLR pipeline [10] and ideas from neural style transfer to construct our self-supervised image embeddings, but we focus on using the embeddings to explore relationships in other data.

Aligning word embeddings. One of our approaches to constructing metaphors is based on mapping between different embedding spaces. A related idea is utilized in natural language processing to facilitate machine translation. Given two word embeddings of different languages, a transformation (often linear) can be constructed to map the words of one language onto another. This can be done by using supervised word pairs [38], finding similar strings in both languages [44], or more recently, in an unsupervised fashion by aligning the two distributions [2, 31] (see [42] for a comprehensive survey). We also aim to transfer knowledge by exploiting similarities between two domains, but unlike languages, our domains can share little similarity, making the linear (or any simple) mapping insufficient. Most importantly, we present a conceptual approach to visualization through metaphors, where mapping between embeddings is just one of the many possible implementations.

4 IMPLEMENTATION

Before we continue to the examples of metaphorical visualizations, let us briefly discuss how we implemented the mapping between the data and the concept spaces.

Given a set of data points X and a set of concept points C, our goal is to find a map $M : X \to C$. Because we are mapping to a discrete set of concept points (e.g., a set of images), we seek a discrete assignment, explicitly establishing correspondences between the data points and valid concept points. Depending on the type of metaphor, the map needs to satisfy some constraint, e.g., for distance-based metaphors, the mapping has to be distance-preserving. We can express this constraint as a loss function that should be minimized by the mapping. For the **distance-based metaphors**, this function is a sum of squared differences between pairwise distances in the two spaces:

$$\min_M \; E(M) \text{ with } E(M) = \sum_{i,j} \left(d(x_i, x_j) - d(M(x_i), M(x_j))\right)^2. \quad (1)$$

Depending on the application, M can be constrained to be injective (i.e., mapping to unique concepts). We specify the same distance function d for both spaces, but different functions could be used if normalized appropriately. Note that Eq. 1 is very similar to the Multidimensional Scaling objective [36], but in a discrete formulation that makes it much harder. This is a necessary complication because most interesting concept spaces are discrete (e.g. words).

Unfortunately, this discrete assignment problem is very challenging because this is a general case of the Quadratic Assignment Problem [32]. The exact solution for our spaces is intractable, so we use simulated annealing [29] to compute an approximate solution.

We construct the **attribute-based mapping** by solving a Linear Assignment Problem (LAP). We define the cost of assigning a data point x_i to a concept point c_j as the MSE between the data and concept attribute vectors, thus the cost matrix C for the LAP is:

$$C = \left[c_{ij} = \left(\bar{x_i} - \bar{c_j}\right)^2\right] \in \mathbb{R}^{|X| \times |C|}. \quad (2)$$

Here $\bar{x_i}$ and $\bar{c_j}$ are the vectors of normalized data and concept attributes, constructed according to which data attribute should be mapped to which concept attribute.

The **hybrid mapping** is a straightforward extension of the distance-based method. Now the total cost of an assignment from Eq. 1 also needs to include the linear attribute cost from Eq. 2 and becomes:

$$E(M) = \sum_i \left[c_{x_i, M(x_i)} + \lambda \sum_j \left(d(x_i, x_j) - d(M(x_i), M(x_j))\right)^2\right]. \quad (3)$$

Here the first term is the attribute-based cost of mapping each data point x_i to a concept $M(x_i)$. And the second term is the distance-based cost from Eq. 1 that captures the difference between the data and the concept distance for every pair of data points. The coefficient λ is used to control their relative importance. You can find additional implementation details, metaphor examples and our qualitative study in supplemental materials at https://osf.io/jbtkq (https://doi.org/10.17605/osf.io/jr2gc).

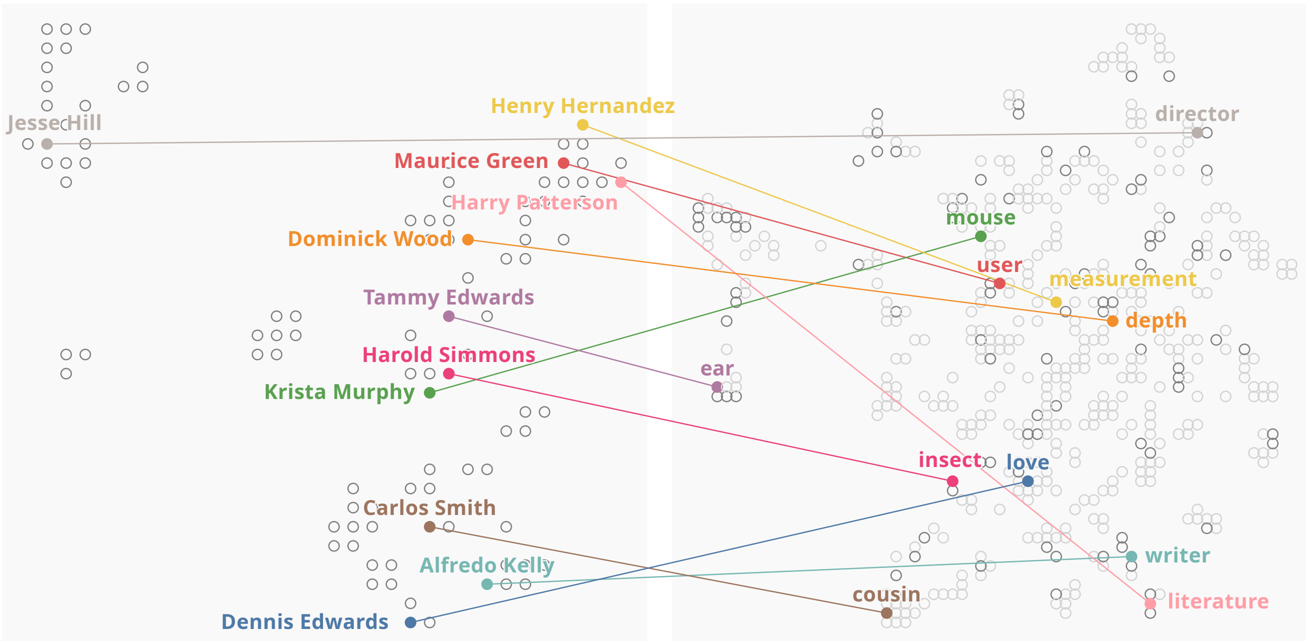


Figure 1: Mapping VIS authors to English nouns. We show a UMAP projection of the author embedding (left) and the word embedding (right), and plot lines to visualize a few pairs from the resulting mapping. Some similarity relationships are present in the author projection (Maurice Green → 'user', Henry Hernandez → 'measurement'), but some are seen only in the concept projection (Harry Patterson → 'literature', Alfredo Kelly → 'writer'). And some of the more subtle similarities can only be noticed from the word themselves, e.g. Harry Patterson → 'literature' and Dennis Edwards → 'love'.

5 DISTANCE-BASED MAPPING

Here we describe examples of metaphorical mappings that preserve distances in the data and the concept spaces. We chose to focus on machine-learning embeddings for our data and concept spaces, but anything that has a distance function can be used for this approach. Throughout this section, we use the publication records of CHI, VIS and SIGGRAPH authors as our data. Initially, we constructed all results using their names and bio photos, but to avoid revealing personal information in this paper, we refer to each author using a randomly generated name and portrait.

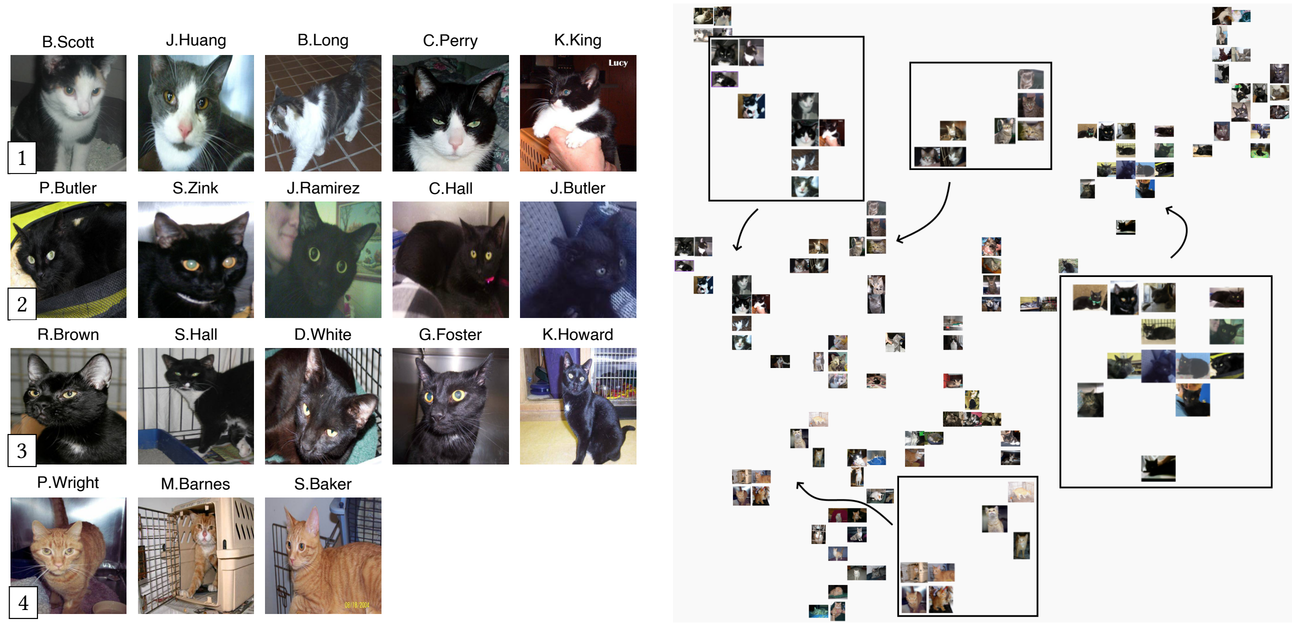
5.1 Authors to Words

In this first example, we illustrate how VIS authors could be explored metaphorically by mapping them to English nouns. The data space is an embedding of authors, which is learned similarly to word2vec [39] from the VisPubData dataset [23]. Our concept space consists of 500 common English nouns, which we passed to a pre-trained word-embedding model. For our metaphor, we map the top 100 IEEE VIS authors to nouns. Again, we used randomly generated names for the privacy of the authors.

We visualize the mapping in Fig. 1. We present each of the two spaces as a scatterplot of the UMAP-projected points [35]. Here, we also connect data points to their assigned concepts with lines. While showing the projections is not necessary for our approach, it helps us compare the positional and the metaphorical mappings. The common co-authors were assigned to strongly related words, e.g. Maurice Green → 'user' and Henry Hernandez → 'measurement' (cosine 0.61), similarly Krista Murphy → 'mouse' and Harold Simmons → 'insect' (cos 0.64). Points that are not related are appropriately mapped to unrelated words, for instance Krista Murphy → 'mouse', Jesse Hill → 'director' (cos -0.45). There are also pairs, e.g. Harry Patterson → 'literature' and Dennis Edwards → 'love', that share similarity (cos 0.53), but it is lost in the projections, revealed only through the metaphorical mapping.

Importantly, the mapping works not only for points highlighted in Fig. 1 but for the whole dataset. If we now consider the 50 most frequent authors, we can "wander" through the space, following pairs of related authors (about 0.4-0.7 cosine), e.g.: Maurice Green → 'user', Adam Varma → 'engine', Harold Taylor → 'mixture', kellie Jackson → 'salad', Harvey Hill → 'ratio', Ben patterson → 'efficiency', Marilyn Huang → 'interaction' and back to Maurice Green → 'user'. A single word like 'mouse' (Krista Murphy), can express relationships to 'user' and 'device', but also to 'insect' and 'bird'. This flexibility of the word metaphor allows it to preserve some of the global relationships. In out study (supplemental materials, see Sec. 4), people reported that the word space requires time to interpret, but they were generally able to find thematic word clusters and sometimes the finer connections between the words.

This example is meant to introduce the idea of the metaphorical mapping, but also to illustrate some of its strengths and weaknesses. Of course, mapping data to words is not as accurate and reliable as



(a) **(b)**

Figure 2: Mapping CHI authors to cat images. a: Groups of similar-looking cats were mapped to related authors, e.g. the black-and-white cats ($\boxed{1}$: Bruce Sanchez, Jesse Hill, Brian Lee, etc.) or the black cats ($\boxed{2}$: Peter Butler, Simon Zink Jeremy Ramirez, etc.). b: A UMAP projection of the frequent author vectors, drawn as cats. We see many clusters of similar cats.

traditional visualization. However, words can be concise and engaging, giving us the ability to describe a person's research interests with a single term. This can be advantageous when the main goal is not to convey facts as accurately as possible, but to engage the audience in casual data exploration. For example, imagine printing a single keyword on badges at a conference social event, providing a fun way of encouraging interaction and guiding people to others with shared interests.

5.2 Authors to Cats

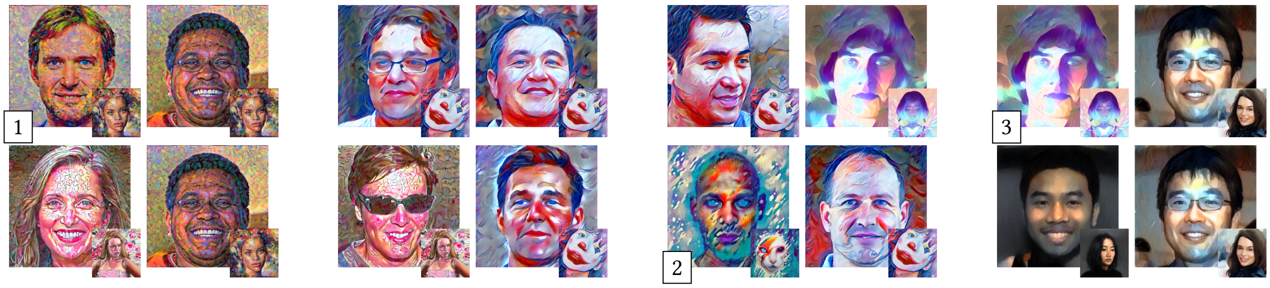
In our second example of a distance-based mapping, we construct a space of CHI authors and use cat images as our concepts. For the data space, we obtained an author-keyword matrix from Microsoft Academic and applied a sparse Singular Value Decomposition (SVD) to compute the embedding for the 100 most frequent authors. To construct a cat embedding, we took the cat images from the "Dogs-vs-Cats" dataset [27] and trained a model using SimCLR [10], with ResNet18 [21] as the encoder architecture. We sampled 1000 cat images and their feature vectors as our concept space.

In Fig. **??**, we show the assigned cat images for some of the frequent authors in our data. Although cat similarity can be more ambiguous to interpret, there are several interesting clusters. For example, there is a set of black-and-white cats ($\boxed{1}$): Bruce Sanchez, Jesse Hill, Brian Lee, etc. that contains related authors working in visualization and visual analytics (cos 0.62-0.83). Similarly, there is a large group of black cats that feature many similar authors sharing a connection through mobile and ubiquitous computing ($\boxed{2}$): Peter Butler, Simon Zink, Jeremy Ramirez, etc. (cos 0.57-0.90). The mapping also utilizes other features, producing a different but related cluster of black cats with a cage background ($\boxed{3}$). In this cluster we find researchers whose topics commonly include user interfaces and multimedia: Ramon Brown, Sara Hall, Darrin White, etc. (cos 0.45-0.79). Strongly dissimilar to the above are the white and ginger cats. The latter ($\boxed{4}$) represent some of the authors working in psychology and sociology, e.g. Phillip Wright, Mary Barnes, Sam Baker (cos 0.63-0.69). We show the author projection in Fig. **??**, replacing the markers with the cat images. On this scatterplot, we can also confirm that strongly-related authors from the same cluster are assigned similar cat images.

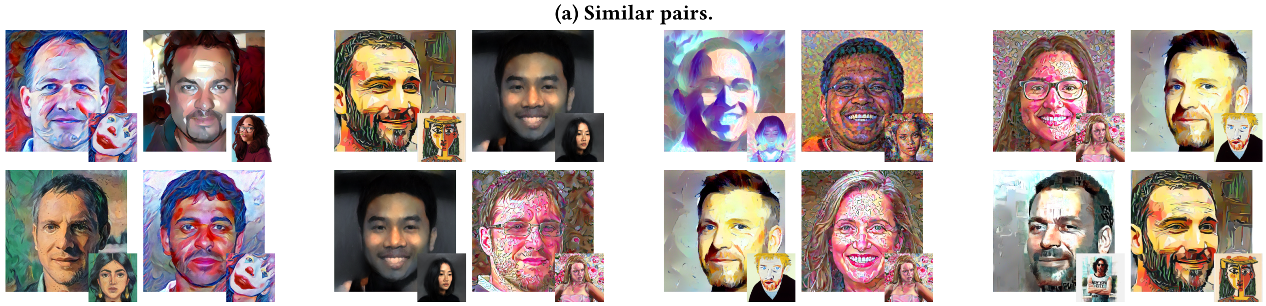
Overall, we found that our metaphorical mapping produces meaningful results for image embeddings. Our user study (see Sec. 4) indicated that people are generally able to find similar cats, with the color being the most prominent feature. This example is meant to demonstrate that the idea of metaphors can be applied to many types of data, and we hope that it can spark other creative applications. In fact, in the next section, we continue to build upon this image mapping method to stylize author photographs to implicitly encode author similarity.

5.3 Authors to Visual styles

Continuing with the idea of image metaphors, we can not only assign a specific image to each author, but use just some of its properties to encode the metaphor. In this example, we will use neural style transfer to encode the similarity of SIGGRAPH authors



(a) Similar pairs.



(b) Dissimilar pairs.

Figure 3: Mapping SIGGRAPH authors to visual styles to provide an ambient visualization of their research interests. We map each author to a style donor image, such that authors with related publications are mapped to similar (or even identical) styles. We then transfer the style onto the author's portrait (we use artificial images) to seamlessly encode their interests. In (a), we show a sampling of related author pairs, where similarity can be encoded by using an identical style ($\boxed{1}$), styles with similar colors ($\boxed{2}$) or strokes ($\boxed{3}$). And in (b) we show pairs of unrelated authors, which were assigned significantly different styles. Such avatars could be used, for example, during an online conference to unobtrusively foster communication.

into the artistic style of their portrait images. We use images generated by StyleGAN2 [28] to anonymize the authors images. The author embedding vectors are learned from a dataset of SIGGRAPH papers with the method from Sec. 5.1. Similarly to our cat metaphor, we perform a mapping between the author vectors and an image embedding of style donor images. We construct an image distance metric that emphasizes the style of the image (rather than its content), making modifications to our model from Sec. 5.2, most importantly, not using the encoder output directly, but extracting a Gram matrix of its layers' activations (we follow [17] in what constitutes style information).

For the metaphor itself, we construct a distance-based mapping between the author and style vectors, mapping 100 most frequent authors to a small sample of 16 style images. We deliberately use a small number of style images and allow duplicate assignments to make it easier to distinguish style similarity. Then, we perform the style transfer for each author image with the method of Gatys et al. [17].

The styled author portraits are presented in Fig. 3. In the top half, we show samples of similar author pairs (75th percentile and above). Authors with stronger similarity are assigned identical styles ($\boxed{1}$), making them particularly easy to distinguish. But other similar authors are also distinguishable through the similarities in the color scheme ($\boxed{2}$) or brushwork ($\boxed{3}$). And in the bottom half, we see that the most dissimilar authors (25th percentile and below) were mapped to significantly different visual styles.

Compared to the pure image metaphor from Sec. 5.2, mapping to visual styles allows more control over the final representation. Here we can fix the content of an image and use the metaphor to only alter its style, creating an implicit visualization of the metadata. Once again, the main strength of this approach is that it can be adapted to the application at hand and can provide a seamless way for users to engage with the data. For example, imagine generating stylized avatars for participants of an online conference. The users could be provided with a few options to tweak the result to their liking and then implicitly communicate their research topics to connect with the other participants.

6 ATTRIBUTE-BASED MAPPING

The idea of the attribute-based mapping is that when we have tabular data with directly interpretable attributes, we can explicitly define which concept attribute should represent which data attribute. For example, we could map movies onto stars, such that the star's apparent brightness represents the user rating of a movie. Compared to the distance-based mapping, this requires additional design choices, but provides more control over the result and leads to a more transparent metaphor.

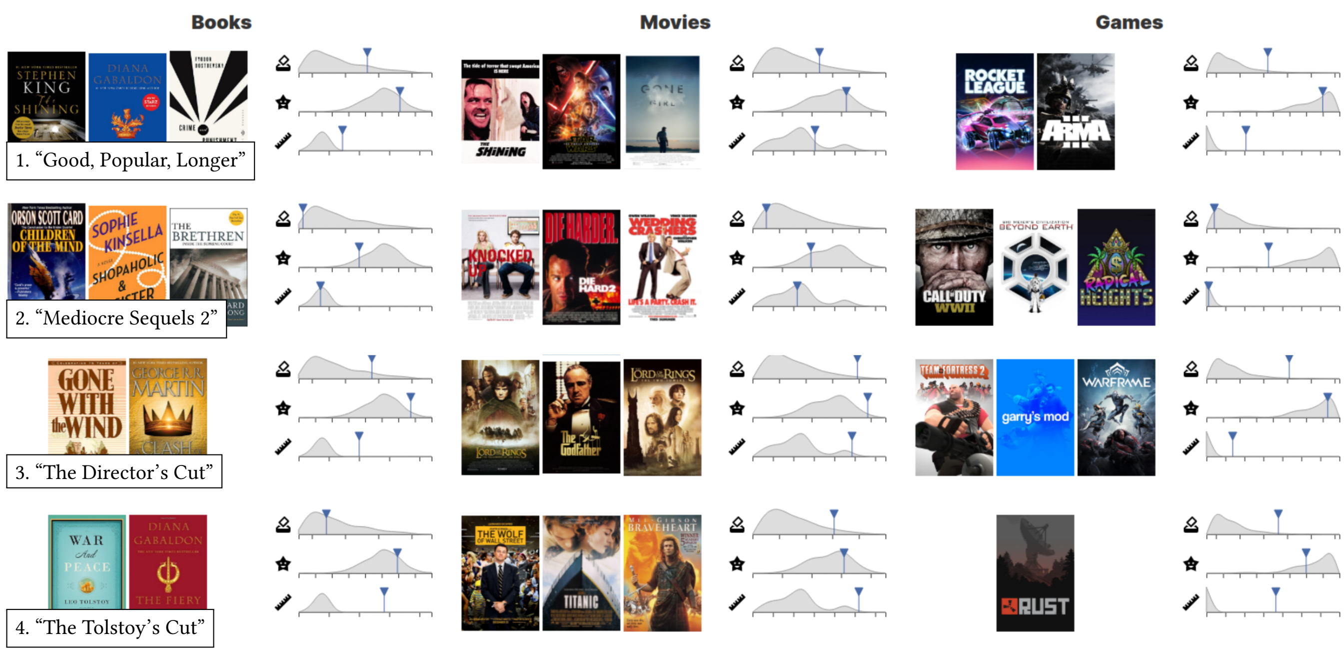


Figure 4: Attribute-based mapping of book clusters to clusters of movies and games. The works with similar relative popularity, rating and length are matched together. Each row shows a triplet of matched clusters, and where each cluster falls in the overall distribution of popularity ( ), rating ( ) and length ( ). This metaphor successfully connects similar archetypes across all three domains. For example, we see the "Tolstoy's cut" category of extremely long, but moderately rated "War and Peace", "Titanic" and "Rust" ($\boxed{4}$).

6.1 Books to Movies and Games

We demonstrate our attribute-based mapping with a metaphor between popular books, movies and video games. All three domains are represented by tabular data with directly interpretable attributes such as user rating, release date, etc. We make the metaphor even more intuitive by mapping between similar attributes, e.g., matching the book's user rating to the movie's user rating.

We use a dataset of books from Goodreads [12], the movie dataset comes from IMDb [33] and the game data is from Steam [1]. For all three domains, we take the 500 entries with the most user ratings (i.e., the most popular). We map rating to rating, popularity to popularity and page length to movie duration and average playtime.

We discuss the results of this item-to-item mapping in the supplemental materials (Fig. S1). However, we found that the most interesting way of applying the attribute-based mapping is to perform clustering first. The mapping is then performed between the clusters, producing both a multi-way assignment and generating distinct "categories" of analogous items across the three domains.

The results are presented in Fig. 4. In each row, we display three clusters (one from each domain) that were mapped to each other. For each cluster, we show three examples and plot where the cluster centroid (blue marks) is located in the overall distribution of each attribute (gray outline). In the first row ($\boxed{1}$), we see a cluster with works that are quite popular, positively rated and have above-average length. For books, we have "The Shining" and "Outlander" with 600+ pages, matched to the movie "The Shining" and popular games like "Rocket League" and "Arma 3". We observe that the mapping is preserving all three attributes well, resulting in a richer metaphor. Next ($\boxed{2}$), we have the opposite situation, with items that are not so popular, poorly rated (compared to the other 500 items) and are on the shorter side. Unsurprisingly, many of them are sequels. Another interesting example is an outlier cluster of popular, very well rated and very long works ($\boxed{3}$): George R.R. Martin's "Clash of Kings", "The Lord of the Rings" films, "The Godfather", "Team Fortress 2" and "Warframe". All well-known, beloved and very long (or played a lot in the case of games). And the last cluster ($\boxed{4}$) has even longer works that have positive but not an outstanding rating. Here we see "War and Peace", "Titanic" and "Rust", all extremely long and with favorable user ratings, but not the highest possible. These last two clusters are outlier cases, nevertheless, we are still able to construct an appropriate metaphor, even when dealing with the extremes of all three distributions.

In summary, we see that despite the simplicity of the attribute-based mapping, we are able to generate accurate and engaging associations between different domains. Its particular strength lies in the control that we have over the metaphor and its resulting transparency. The ultimate application of this metaphor could be, for example, in recommendation systems. With the knowledge of which works the user has read/watched/played, we can generate a personalized cross-media metaphor, also taking into the account the user's own ratings. So if you liked that one book that everyone else hated, we can use it as a metaphor to describe an unpopular movie that you personally might enjoy, rather than just suggesting an unknown movie with "bad" rating.

7 HYBRID MAPPING

In this section, we will combine the methods from Sec. 5 and Sec. 6 to preserve both the distances as well as the relative attribute values. One scenario where preserving both could be helpful is when we want to control a particular aspect of a distance-based metaphor, e.g., to assign frequently used words to the more frequent authors in our metaphor from Sec. 5.1. Another important use case arises when using attribute-based mapping with concepts that have inherent spatial information. We describe such a scenario below, where we map movies to stars in the night sky.

7.1 Movies to Stars

We demonstrate the hybrid mapping by assigning popular movies to bright stars. With this metaphor, we generate an illustrated map of the night sky, inviting the users to explore the data and build connections between movies and stars.

For our data space, we use a list of 200 movies from IMDB with the highest number of votes (popularity), cross-referenced with the MovieLens Tag Genome Dataset [47]. With the tag data, we build a movie-tag matrix and perform SVD to construct a movie embedding. And for the concept space, we use a list of 400 brightest stars in the night sky.

Next, we need to define the mapping, and here we must consider how it will be presented to the user. The stars have natural spatial positions that we can exploit to encode more information into the visualization. We accomplish this by using our hybrid mapping approach to add additional distance-based costs. For the stars, we compute the Euclidean distance in the display space, and for the movies, we apply UMAP to first project them into a two-dimensional space and then compute the Euclidean distance. We apply this pre-projection step rather than compute the distances in the high-dimensional space because a neighbor-preserving projection works better when mapping to the low-dimensional space of 2D positions. For the attributes, we map the average movie rating to the star brightness (apparent magnitude) so that highly-rated movies will correspond to the brightest stars.

The results are presented in Fig. 5 and in the supplemental video. We render the stars and the constellations with D3-Celestial [16] and mark all the stars that were assigned a movie. The posters are shown only for the most popular films to avoid clutter. We also show magnified images for several clusters.

First, we observe that the movie similarity was properly encoded as the star distances. For example, we see a cluster of Disney/Pixar animated films (purple, "The Lion King", "Up") next to the Boötes constellation of Miyazaki animes (teal, "Spirited Away", "My Neighbor Totoro"); a cluster of older western and mafia movies (orange, "Once Upon a Time in the West", "The Godfather"); and a constellation of Tarantino and similar crime films (green, "Pulp Fiction", "Snatch"). Inspecting different regions of the sky, we also see that the films with the highest rating are mapped to the brightest stars (relative to the other popular films). The highly-rated "The Godfather" is mapped to the brightest star of the region – Canopus, while the nearby "Goodfellas" is assigned to the dimmer Adhara.

Overall, we believe that the mapping captures the metaphor of the "movie night sky panorama" and generates some memorable connections, like Boötes being the anime constellation and Leo representing films about war. Informally, we found it much more engaging to explore both stars and movies under a joint metaphor than as separate datasets. It shows that sometimes the metaphors could be even more fun when the user has some knowledge of both spaces, telling stories and making associations across them. This could be used, for example, for science communication or to connect to a particular audience. Furthermore, together with the Authors-to-Styles metaphor (Sec. 5.3), this application also demonstrates how the metaphors can influence the visualization itself, mapping to visual attributes (positions, in this case) as well as abstract data (ratings) to construct the final representation.

8 DISCUSSION

Our goal with this paper was to demonstrate the flexibility and creativity of metaphorical visualization, so we focused on constructing a wide range of metaphor examples. Here, we discuss our general takeaways from building data metaphors and their possible future applications.

One of the most important design considerations is making the metaphor clear and intuitive. For example, in our books-movies-games metaphor (Sec. 6) we map between semantically identical (user rating) or analogous (length) attributes. Mapping the user rating to the number of actors would be possible but would likely feel unintuitive. The metaphor should also avoid "metaphorical artifacts", which occur when we attribute to data some concept properties that are not a part of the metaphor. In our movies to stars mapping (Sec. 7), we originally did not consider distances between stars in the metaphor, but this led to interpreting movies mapped to nearby stars as related. As a response, we incorporated the distances into the metaphor to avoid false associations.

In general, when clear interpretation is important, attribute-based and hybrid mappings are the more appropriate choice, as they allow a more direct control of the metaphor. We see their most promising applications in data storytelling and infographics, where the designer can define and adjust the metaphor to tell a story. For example, imagine designing an interactive beginner's guide to books for movie buffs, connecting not only rating and popularity, but also genres, time periods and target audiences. The metaphor could help connect more personally to the reader's movie tastes, beyond simply showing the best rated of all time. And in science communication, metaphors can help the audience make more memorable connections, for instance, one could map stars and galaxies to pokemons, making the scientific content more engaging and memorable for children (and adults).

The distance-based metaphors are more ambiguous, but are also richer and more flexible. We see them as being most appropriate in casual personal contexts, e.g., as the initial "hook" into further data exploration. We already mentioned that the author-word metaphor could be used at a conference event to entice socializing. We could also change the set of words to adapt to the application context, e.g., generating aliases for an online book/movie/gaming community using words related to the setting of the fictional world and encoding their tastes and hobbies. With a different similarity metric, we could

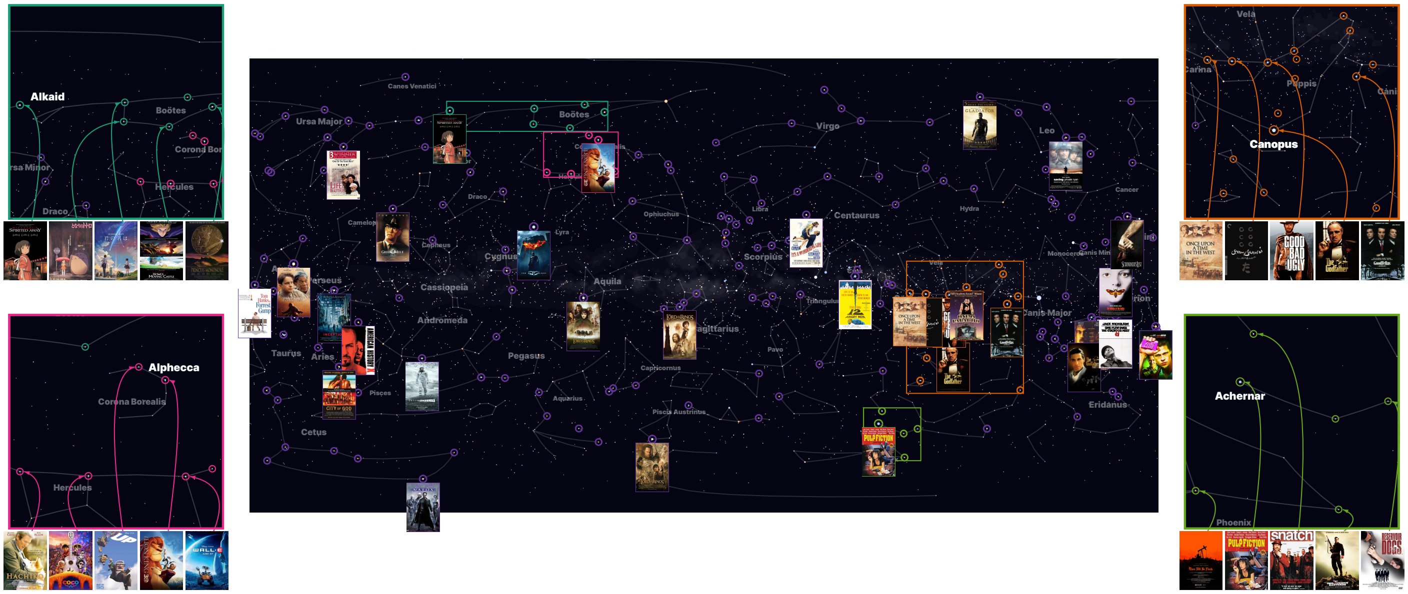


Figure 5: The metaphorical mapping of popular movies to stars in the night sky. We assign well-rated movies to brighter stars, while also attributing related movies to neighboring stars. Users can explore this engaging infographic to build connections between stars and movies and to find out more about both in the process. For example, in the top-left corner, we see Miyazaki's animated films (in green, "My Neighbor Totoro", "Howl's Moving Castle", etc.) mapped to the Boötes constellation. Here the brightest star Alkaid was assigned to "Spirited Away", suggesting that it is the highest-rated of the films. Just below, the animated film classic "The Lion King" (in purple) became Alphecca – the jewel of the northern crown (Corona Borealis). And the exceptionally positively rated "The Godfather" became the second-brightest star in the sky – Canopus, surrounded by the mafia, western and samurai movies. See the supplemental materials for a video and a full-page version of this figure.

even map to words not based on the semantics, but pronunciation, "rhyming" related people.

This highlights the strength of metaphors in ambient "visualization", i.e., unobtrusive data enrichment of existing applications. We demonstrated this with our styled portraits, which could be used during online group communication to help find people with similar interests. Image metaphors could replace the randomly generated avatars (e.g., used by discord and github) with an abstract image that actually reflects the user's profile. Generative image models could be used to directly produce the suitable images, instead of relying on a fixed dataset. Imagine taking this concept into the real world too, for instance, printing ML-generated art on T-shirts for attendees of a music festival, encoding their musical tastes with image similarity.

9 CONCLUSION

In this paper, we presented an approach to using metaphors for visualization and implemented a number of its applications. The examples were chosen to display the flexibility of the approach, to discuss its main design considerations and to hopefully be engaging for the reader. We are excited about the idea of metaphorical visualization and believe that metaphors could find their usage in many informal and personalized applications. Overall, the goal of this paper is to put the idea out to the community and to potentially inspire others to create further metaphors and use cases.

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REFERENCES

[1] Alexander Antonov. 2019. Steam Games Complete Dataset. https://kaggle.com/trolukovich/steam-games-complete-dataset.

[2] Mikel Artetxe, Gorka Labaka, and Eneko Agirre. 2018. A Robust Self-Learning Method for Fully Unsupervised Cross-Lingual Mappings of Word Embeddings. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Melbourne, Australia, 789–798. https://doi.org/10.18653/v1/P18-1073

[3] Dominikus Baur, Frederik Seiffert, Michael Sedlmair, and Sebastian Boring. 2010. The Streams of Our Lives: Visualizing Listening Histories in Context. *IEEE Transactions on Visualization and Computer Graphics* 16, 6 (Nov. 2010), 1119–1128. https://doi.org/10.1109/TVCG.2010.206

[4] Sean Bell and Kavita Bala. 2015. Learning Visual Similarity for Product Design with Convolutional Neural Networks. *ACM Transactions on Graphics* 34, 4 (July 2015), 98:1–98:10. https://doi.org/10.1145/2766959

[5] Hrvoje Benko and Steven Feiner. 2007. Balloon Selection: A Multi-Finger Technique for Accurate Low-Fatigue 3D Selection. In *2007 IEEE Symposium on 3D User Interfaces*. https://doi.org/10.1109/3DUI.2007.340778

[6] Kalina Borkiewicz, AJ Christensen, Helen-Nicole Kostis, Greg Shirah, and Ryan Wyatt. 2019. Cinematic Scientific Visualization: The Art of Communicating Science. In *ACM SIGGRAPH 2019 Courses (SIGGRAPH '19)*. Association for Computing Machinery, New York, NY, USA, 1–273. https://doi.org/10.1145/3305366.3328056

[7] Kalina Borkiewicz, A J Christensen, Ryan Wyatt, and Ernest T. Wright. 2020. Introduction to Cinematic Scientific Visualization. In *ACM SIGGRAPH 2020 Courses (SIGGRAPH '20)*. Association for Computing Machinery, New York, NY, USA, 1–267. https://doi.org/10.1145/3388769.3407502

[8] Michelle A. Borkin, Azalea A. Vo, Zoya Bylinskii, Phillip Isola, Shashank Sunkavalli, Aude Oliva, and Hanspeter Pfister. 2013. What Makes a Visualization Memorable? *IEEE Transactions on Visualization and Computer Graphics* 19, 12 (Dec. 2013), 2306–2315. https://doi.org/10.1109/TVCG.2013.234
[9] Benoît Bossavit, Asier Marzo, Oscar Ardaiz, Luis Diaz De Cerio, and Alfredo Pina. 2014. Design Choices and Their Implications for 3D Mid-Air Manipulation Techniques. *Presence: Teleoperators and Virtual Environments* 23, 4 (Nov. 2014), 377–392. https://doi.org/10.1162/PRES_a_00207
[10] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. 2020. A Simple Framework for Contrastive Learning of Visual Representations. *arXiv:2002.05709* (2020). arXiv:2002.05709
[11] Florian Daiber, Eric Falk, and Antonio Krüger. 2012. Balloon Selection Revisited: Multi-Touch Selection Techniques for Stereoscopic Data. In *Proceedings of the International Working Conference on Advanced Visual Interfaces (AVI '12)*. Association for Computing Machinery, New York, NY, USA, 441–444. https://doi.org/10.1145/2254556.2254641
[12] Soumik Ranjan Dasgupta. 2019. Goodreads-Books. https://kaggle.com/jealousleopard/goodreadsbooks.
[13] Carl Doersch, Abhinav Gupta, and Alexei A. Efros. 2015. Unsupervised Visual Representation Learning by Context Prediction. In *Proceedings of the IEEE International Conference on Computer Vision*. 1422–1430.
[14] Carl Doersch and Andrew Zisserman. 2017. Multi-Task Self-Supervised Visual Learning. *arXiv:1708.07860 [cs]* (Aug. 2017). arXiv:1708.07860 [cs]
[15] Alexey Dosovitskiy, Jost Tobias Springenberg, Martin Riedmiller, and Thomas Brox. 2014. Discriminative Unsupervised Feature Learning with Convolutional Neural Networks. In *Advances in Neural Information Processing Systems 27*. Curran Associates, Inc., 766–774.
[16] Olaf Frohn. 2017. D3 Celestial. https://github.com/ofrohn/d3-celestial.
[17] Leon A. Gatys, Alexander S. Ecker, and Matthias Bethge. 2015. A Neural Algorithm of Artistic Style. *arXiv:1508.06576 [cs, q-bio]* (Aug. 2015). arXiv:1508.06576 [cs, q-bio]
[18] Lane Harrison, Katharina Reinecke, and Remco Chang. 2015. Infographic Aesthetics: Designing for the First Impression. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15)*. Association for Computing Machinery, New York, NY, USA, 1187–1190. https://doi.org/10.1145/2702123.2702545
[19] Rex Hartson and Pardha Pyla. 2019. Chapter 15 - Mental Models and Conceptual Design. In *The UX Book (Second Edition)*, Rex Hartson and Pardha Pyla (Eds.). Morgan Kaufmann, Boston, 327–340. https://doi.org/10.1016/B978-0-12-805342-3.00015-1
[20] S. Havre, E. Hetzler, P. Whitney, and L. Nowell. 2002. ThemeRiver: Visualizing Thematic Changes in Large Document Collections. *IEEE Transactions on Visualization and Computer Graphics* 8, 1 (Jan. 2002), 9–20. https://doi.org/10.1109/2945.981848
[21] K. He, X. Zhang, S. Ren, and J. Sun. 2016. Deep Residual Learning for Image Recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 770–778. https://doi.org/10.1109/CVPR.2016.90
[22] Dandan Huang, Melanie Tory, Bon Adriel Aseniero, Lyn Bartram, Scott Bateman, Sheelagh Carpendale, Anthony Tang, and Robert Woodbury. 2015. Personal Visualization and Personal Visual Analytics. *IEEE Transactions on Visualization and Computer Graphics* 21, 3 (2015), 420–433. https://doi.org/10.1109/TVCG.2014.2359887
[23] Petra Isenberg, Florian Heimerl, Steffen Koch, Tobias Isenberg, Panpan Xu, Charles D. Stolper, Michael Sedlmair, Jian Chen, Torsten Möller, and John Stasko. 2017. Vispubdata.Org: A Metadata Collection About IEEE Visualization (VIS) Publications. *IEEE Transactions on Visualization and Computer Graphics* 23, 9 (2017), 2199–2206. https://doi.org/10.1109/TVCG.2016.2615308
[24] Clinton L. Jeffery. 2019. *The City Metaphor in Software Visualization*. Václav Skala - UNION Agency. https://doi.org/10.24132/CSRN.2019.2901.1.18
[25] Jason Jerald, Joseph J. LaViola, and Richard Marks. 2017. VR Interactions. In *ACM SIGGRAPH 2017 Courses (SIGGRAPH '17)*. Association for Computing Machinery, New York, NY, USA, 1–105. https://doi.org/10.1145/3084873.3084900
[26] Yongcheng Jing, Yezhou Yang, Zunlei Feng, Jingwen Ye, Yizhou Yu, and Mingli Song. 2020. Neural Style Transfer: A Review. *IEEE Transactions on Visualization and Computer Graphics* 26, 11 (Nov. 2020), 3365–3385. https://doi.org/10.1109/TVCG.2019.2921336
[27] Kaggle. 2014. Dogs vs Cats. https://www.kaggle.com/c/dogs-vs-cats.
[28] Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, and Timo Aila. 2020. Analyzing and Improving the Image Quality of StyleGAN. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. 8107–8116. https://doi.org/10.1109/CVPR42600.2020.00813
[29] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi. 1983. Optimization by Simulated Annealing. *Science* 220, 4598 (May 1983), 671–680. https://doi.org/10.1126/science.220.4598.671
[30] George Lakoff. 1980. *Metaphors We Live By*. University of Chicago Press, Chicago.
[31] Guillaume Lample, Alexis Conneau, Marc'Aurelio Ranzato, Ludovic Denoyer, and Hervé Jégou. 2018. Word Translation without Parallel Data. In *International Conference on Learning Representations*.
[32] Eugene L Lawler. 1963. The Quadratic Assignment Problem. *Management science* 9, 4 (1963), 586–599.
[33] Stefano Leone. 2019. IMDb Movies Extensive Dataset | Kaggle. https://www.kaggle.com/stefanoleone992/imdb-extensive-dataset/version/2.
[34] Zhaoliang Lun, Evangelos Kalogerakis, and Alla Sheffer. 2015. Elements of Style: Learning Perceptual Shape Style Similarity. *ACM Transactions on Graphics* 34, 4 (July 2015), 84:1–84:14. https://doi.org/10.1145/2766929
[35] Leland McInnes, John Healy, and James Melville. 2018. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. *arXiv:1802.03426* (Dec. 2018). arXiv:1802.03426
[36] A. Mead. 1992. Review of the Development of Multidimensional Scaling Methods. *Journal of the Royal Statistical Society* 41, 1 (1992), 27–39. https://doi.org/10.2307/2348634
[37] D. Mendes, F. M. Caputo, A. Giachetti, A. Ferreira, and J. Jorge. 2019. A Survey on 3D Virtual Object Manipulation: From the Desktop to Immersive Virtual Environments. *Computer Graphics Forum* 38, 1 (2019), 21–45. https://doi.org/10.1111/cgf.13390
[38] Tomas Mikolov, Quoc V. Le, and Ilya Sutskever. 2013. Exploiting Similarities among Languages for Machine Translation. *arXiv:1309.4168 [cs]* (Sept. 2013). arXiv:1309.4168 [cs]
[39] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. 2013. Distributed Representations of Words and Phrases and Their Compositionality. In *Advances in Neural Information Processing Systems (NIPS)*. 3111–3119.
[40] Zachary Pousman, John Stasko, and Michael Mateas. 2007. Casual Information Visualization: Depictions of Data in Everyday Life. *IEEE Transactions on Visualization and Computer Graphics* 13, 6 (Nov. 2007), 1145–1152. https://doi.org/10.1109/TVCG.2007.70541
[41] Stephen Richards, Philip Barker, Ashok Banerji, Charles Lamont, and Karim Manji. 2009. The Use of Metaphors in Iconic Interface Design. *Digital Creativity (Intelligent Tutoring Media)* (April 2009). https://doi.org/10.1080/14626269409408345
[42] Sebastian Ruder, Ivan Vulić, and Anders Søgaard. 2019. A Survey of Cross-lingual Word Embedding Models. *Journal of Artificial Intelligence Research* 65 (Aug. 2019), 569–631. https://doi.org/10.1613/jair.1.11640
[43] Joseph P. Sanford, Aaron Tietz, Saad Farooq, Samuel Guyer, and R. Benjamin Shapiro. 2014. Metaphors We Teach By. In *Proceedings of the 45th ACM Technical Symposium on Computer Science Education (SIGCSE '14)*. Association for Computing Machinery, New York, NY, USA, 585–590. https://doi.org/10.1145/2538862.2538945
[44] Samuel L. Smith, David H. P. Turban, Steven Hamblin, and Nils Y. Hammerla. 2016. Offline Bilingual Word Vectors, Orthogonal Transformations and the Inverted Softmax. (Nov. 2016).
[45] Peng Song, Wooi Boon Goh, William Hutama, Chi-Wing Fu, and Xiaopei Liu. 2012. A Handle Bar Metaphor for Virtual Object Manipulation with Mid-Air Interaction. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '12)*. Association for Computing Machinery, New York, NY, USA, 1297–1306. https://doi.org/10.1145/2207676.2208585
[46] Fernanda B. Viegas, Martin Wattenberg, and Jonathan Feinberg. 2009. Participatory Visualization with Wordle. *IEEE Transactions on Visualization and Computer Graphics* 15, 6 (Nov. 2009), 1137–1144. https://doi.org/10.1109/TVCG.2009.171
[47] Jesse Vig, Shilad Sen, and John Riedl. 2012. The Tag Genome: Encoding Community Knowledge to Support Novel Interaction. *ACM Transactions on Interactive Intelligent Systems* 2, 3 (Sept. 2012), 13:1–13:44. https://doi.org/10.1145/2362394.2362395
[48] Anders Ynnerman, Jonas Löwgren, and Lena Tibell. 2018. Exploranation: A New Science Communication Paradigm. *IEEE Computer Graphics and Applications* 38, 3 (May 2018), 13–20. https://doi.org/10.1109/MCG.2018.032421649
[49] Caroline Ziemkiewicz and Robert Kosara. 2008. The Shaping of Information by Visual Metaphors. *IEEE Transactions on Visualization and Computer Graphics* 14, 6 (Nov. 2008), 1269–1276. https://doi.org/10.1109/TVCG.2008.171