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Perceptual Grouping Explains Similarities in Constellations Across Cultures

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Abstract
Cultures around the world organize stars into constellations, or asterisms, and these groupings are often considered to be arbitrary and culture specific. Yet there are striking similarities in asterisms across cultures, and groupings such as Orion, the Big Dipper, the Pleiades, and the Southern Cross are widely recognized across many different cultures. Psychologists have informally suggested that these shared patterns are explained by Gestalt laws of grouping, but there have been no systematic attempts to catalog asterisms that recur across cultures or to explain the perceptual basis of these groupings. Here, we compiled data from 27 cultures around the world and found that a simple computational model of perceptual grouping accounts for many of the recurring cross-cultural asterisms. Our results suggest that basic perceptual principles account for more of the structure of asterisms across cultures than previously acknowledged and highlight ways in which specific cultures depart from this shared baseline.

Keywords
perception, computational modeling, cognitive anthropology, cultural astronomy, categorization, open data, open materials

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Anyone who has tried to learn the full set of 88 Western constellations will sympathize with Herschel (1842), who wrote that "the constellations seem to have been almost purposely named and delineated to cause as much confusion and inconvenience as possible" and that "innumerable snakes twine through long and contorted areas of the heavens, where no memory can follow them" (p. 156). Yet Herschel (1841) and other researchers also have pointed out that there are "well-defined natural groups of conspicuous stars" (pp. 3–4) that have been picked out and named by multiple cultures around the world (Aveni, 2008; Kelley & Milone, 2011; Krupp, 2000a). For example, the Southern Cross is recognized as a cross in multiple cultures (Roe, 2005; Urton, 2005) and is identified as a stingray by the Yolngu of northern Australia (Mountford, 1956), an anchor by the Tainui of Aotearoa/New Zealand (Best, 1922), and a curassow bird by the Lokono of the Guianas (Magaña & Jara, 1982).

Asterisms (e.g., the Southern Cross) are sometimes distinguished from constellations (e.g., the region of the sky within which the Southern Cross lies), but in cross-cultural work, these two terms are often used interchangeably. It is widely acknowledged that asterisms reflect both universal perceptual principles and culture-specific traditions. For example, Urton (1981) notes,

> Almost every culture seems to have recognized a few of the same celestial groupings (e.g., the tight cluster of the Pleiades, the V of the Hyades, the straight line of the belt of Orion), but the large constellation shapes of European astronomy and astrology simply are not universally recognized; the shapes were projected onto the stars because the shapes were important objects or characters in the Western religious, mythological, and calendrical tradition. (p. 5)

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Even groupings as apparently salient as the Southern Cross are not inevitable—some Australian cultures have many names for individual stars but tend not to "connect the dots" to form figured constellations (Cairns & Harney, 2004; Johnson, 2014; Maegraith, 1932).

Although cultural factors are undeniably important, we argue that perceptual factors explain more of the inventory of asterisms across cultures than has previously been recognized. Krupp (2000a) suggests that a "narrow company" (p. 58) of asterisms is common across cultures and lists just four: Orion's Belt, the Pleiades, the Big Dipper, and the Southern Cross. Here, we drew on existing resources to compile a detailed catalog of asterisms across cultures and found that the list of recurring asterisms goes deeper than the handful of examples typically given by Krupp and other authors (Aveni, 1980; Krupp, 2000a, 2000b). To demonstrate that these asterisms are mostly consistent with universal perceptual principles, we present a computational model of perceptual grouping and show that it accounts for many of the asterisms that recur across cultures.

Statement of Relevance

Throughout history, people from many cultures have organized the stars in the night sky into constellations and embedded these constellations in stories. Psychologists have informally suggested that constellations result from a process of perceptual grouping, and here, we systematically explored the extent to which this idea accounts for constellations across cultures. Using data from 27 cultures, we established which constellations appear frequently across cultures and found that the list of recurring constellations extends beyond familiar examples such as Orion and the Big Dipper. We then evaluated a computational model that was designed to capture how humans group stars into constellations. The model groups stars on the basis of proximity and brightness, and these factors alone were enough to account for many of the constellations that recur across cultures. Although constellations are clearly shaped by culture-specific knowledge, our results reveal that basic perceptual factors account for a large set of similarities in constellations across cultures.

A Catalog of Asterisms Across Cultures

Our data set includes 22 systems drawn from the *Stellarium* software package (Version 0.20.1; Chéreau & Stellarium Team, 2020) and five from the ethnographic literature (all sources are listed in the captions of Figs. S16–S42 in the Supplemental Material available online). To allow us to focus on the brighter stars, we preprocessed each system by removing stars fainter than 4.5 in magnitude and then removing all asterisms that included no stars or just one star after filtering. The data span six major regions (Asia, Australia, Europe, North America, Oceania, and South America) and include systems from both oral cultures (e.g., Inuit) and literate cultures (e.g., Chinese). *Stellarium* currently includes a total of 42 systems, but we excluded 20 because they were closely related to a system already included or because their documentation was not sufficiently grounded in the scholarly literature. Most of our sources specify asterism figures in addition to the stars included in each asterism, but we chose not to use these figures because they can vary significantly within a culture and because they were not available for all cultures. Some of our analyses did not require asterism figures, but for those that did, we used minimum spanning trees computed over the stars within each asterism.

Figure 1a shows a consensus system generated by overlaying minimum spanning trees for asterisms from all 27 cultures. The lines (edges) in the plot join stars, and the thickness of these edges indicates the extent to which cultures group these stars together. Thick edges indicate stars that are grouped by many cultures. The most common asterisms include familiar groups such as Orion's Belt, the Pleiades, the Hyades, the Big Dipper, the Southern Cross, and Cassiopeia. The plot also highlights asterisms such as Corona Borealis, Delphinus, and the head of Aries that are discussed less often but nevertheless picked out by multiple cultures. All of these asterisms and more are listed in Table 1, which ranks 36 asterisms on the basis of how frequently they recur across cultures (an extended version of the table appears as Table S2 in the Supplemental Material).

The ranking in Table 1 is based on a quantitative approach that allows for partial matches between asterisms in different cultures. We first defined the match between an asterism a and a reference asterism r as follows:

$$\mathrm{match}(a,r) = \max\left(\frac{|a \cap r| - |a \setminus r|}{|r|}, 0\right), \qquad (1)$$

where $|a \cap r|$ is the number of stars shared by a and r, $|a \setminus r|$ is the number of stars in a that are not shared by r, and $|r|$ is the number of stars in r. The function attains its maximum value of 1 when a and r are identical. There are two ways in which a can differ from r: It can include extraneous stars, and it can fail to include some of the stars in r. The match function penalizes

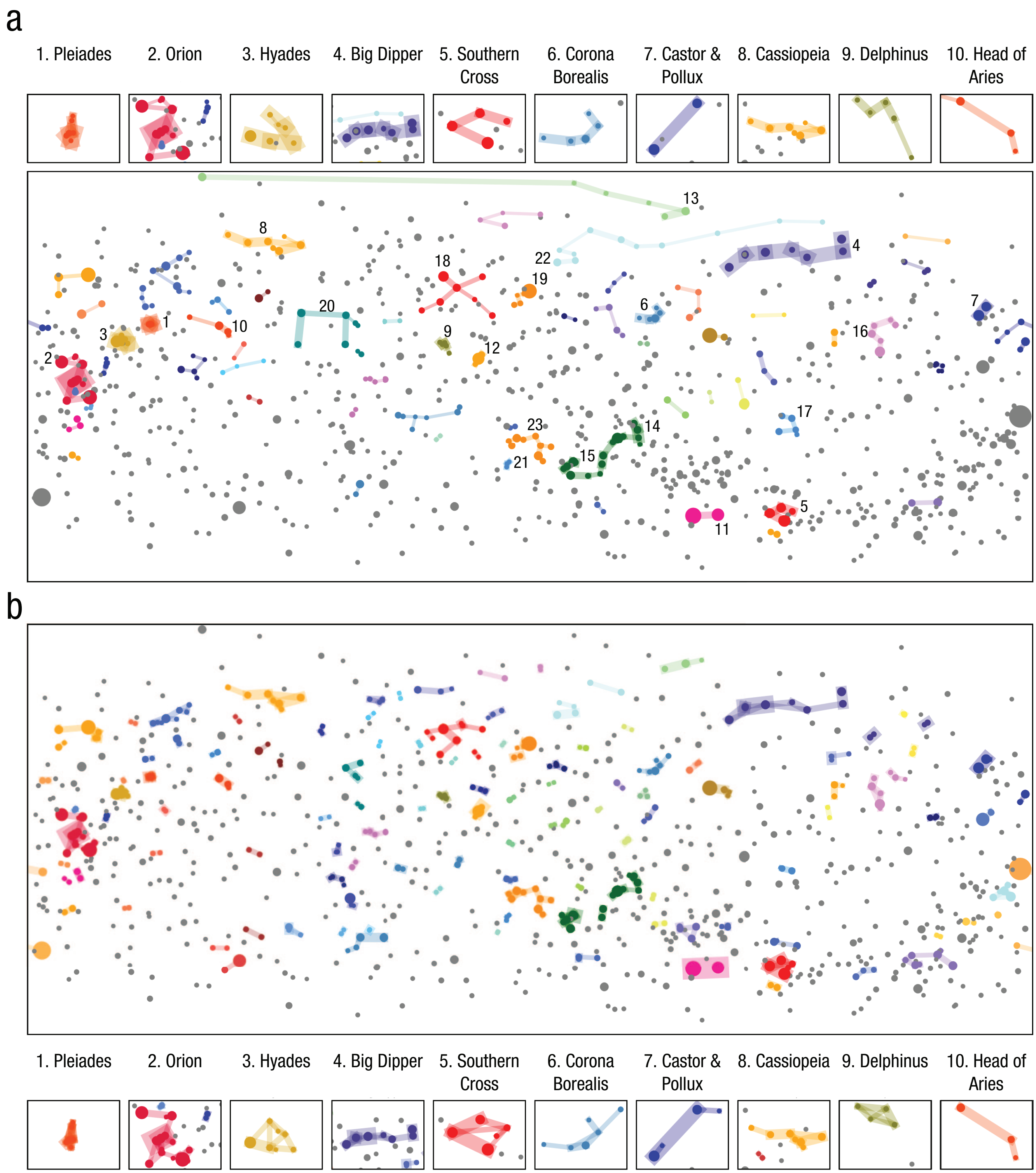

Fig. 1. Common asterisms across cultures (a) compared with model asterisms (b). The consensus system in (a) was created by overlaying minimum spanning trees for all asterisms in our data set of 27 cultures. The width of the line (edge) connecting two stars indicates the number of times that edge appears across the entire data set. Thick edges indicate stars that are grouped by many cultures, and edges that appear three or fewer times are not shown. Node sizes indicate apparent star magnitudes, and only stars with magnitudes brighter than 4.5 have been included. Insets show 10 of the most common asterisms across cultures, and numbers greater than 10 identify additional asterisms mentioned in the text or Table 1: Southern Pointers (11), shaft of Aquila (12), Little Dipper (13), head of Scorpius (14), stinger of Scorpius (15), sickle in Leo (16), Corvus (17), Northern Cross (18), Lyra (19), square of Pegasus (20), Corona Australis (21), head of Draco (22), and teapot in Sagittarius (23). Asterisms according to the graph clustering model ($n = 320$) are shown in (b). The model assigns a strength to each edge in a graph defined over the stars; here, the strongest 320 edges are shown. Edge widths are proportional to the strengths assigned by the model.

Table 1. Common Asterisms Across Cultures

Number	Human score	Weighted human score	Model score	Stars	Description
1	.66	.73	1.0	25EtaTau, 17Tau, 19Tau, 20Tau, 23Tau, 27Tau	Pleiades
2	.65	.64	1.0	34DelOri, 46EpsOri, 50ZetOri	Orion's Belt
3	.61	.52	1.0	87AlpTau, 54GamTau, 61Del1Tau, 74EpsTau, 78The2Tau	Hyades
4	.58	.47	.88	50AlpUMa, 48BetUMa, 64GamUMa, 69DelUMa, 77EpsUMa, 79ZetUMa, 85EtaUMa	Big Dipper
5	.43	.4	1.0	Alp1Cru, BetCru, GamCru, DelCru	Southern Cross
6	.38	.27	.83	5AlpCrB, 3BetCrB, 8GamCrB, 13EpsCrB, 4TheCrB	Corona Borealis
7	.35	.28	1.0	66AlpGem, 78BetGem	Castor and Pollux
8	.35	.34	.45	58AlpOri, 24GamOri, 34DelOri, 46EpsOri, 50ZetOri	
9	.31	.35	.6	34DelOri, 46EpsOri, 50ZetOri, 44IotOri, 42Ori	Orion's Belt and Sword
10	.31	.25	.56	50AlpUMa, 48BetUMa, 64GamUMa, 69DelUMa, 77EpsUMa, 79ZetUMa, 85EtaUMa, 1OmiUMa, 29UpsUMa, 63ChiUMa, 23UMa	
11	.3	.22	.71	18AlpCas, 11BetCas, 27GamCas, 37DelCas, 45EpsCas	Cassiopeia
12	.3	.35	1.0	9AlpDel, 6BetDel, 12Gam2Del, 11DelDel	Delphinus
13	.28	.23	.38	11AlpDra, 50AlpUMa, 48BetUMa, 64GamUMa, 69DelUMa, 77EpsUMa, 79ZetUMa, 85EtaUMa, 23UMa, 26UMa, 12Alp2CVn	
14	.27	.25	.75	46EpsOri, 50ZetOri, 48SigOri	
15	.24	.21	1.0	13AlpAri, 6BetAri, 5Gam2Ari	Head of Aries
16	.24	.22	1.0	53AlpAql, 60BetAql, 50GamAql	Shaft of Aquila
17	.24	.34	1.0	Alp1Cen, BetCen	Southern Pointers
18	.23	.33	1.0	AlpCrA, BetCrA, GamCrA	Corona Australis
19	.23	.15	.75	1AlpUMi, 7BetUMi, 13GamUMi, 23DelUMi, 22EpsUMi, 16ZetUMi	Little Dipper
20	.22	.19	1.0	50AlpUMa, 48BetUMa	
21	.22	.22	1.0	8Bet1Sco, 7DelSco, 6PiSco	Head of Scorpius
22	.21	.21	.04	54AlpPeg, 53BetPeg	
23	.21	.2	1.0	35LamSco, 34UpsSco	Stinger of Scorpius
24	.21	.21	1.0	Iot1Sco, KapSco, 35LamSco, 34UpsSco	
25	.2	.17	.75	32AlpLeo, 41Gam1Leo, 17EpsLeo, 36ZetLeo, 30EtaLeo, 24MuLeo	Sickle
26	.2	.15	.83	1AlpCrv, 9BetCrv, 4GamCrv, 7DelCrv, 2EpsCrv	Corvus
27	.19	.18	.56	21AlpSco, 8Bet1Sco, 7DelSco, 6PiSco, 20SigSco	
28	.19	.19	.0	21AlpAnd, 88GamPeg	
29	.18	.16	.58	21AlpSco, 8Bet1Sco, 7DelSco, 26EpsSco, Zet2Sco, Mu1Sco, 6PiSco, 20SigSco, 23TauSco	
30	.18	.13	.33	50AlpCyg, 6Bet1Cyg, 37GamCyg, 18DelCyg, 53EpsCyg, 21EtaCyg	Northern Cross
31	.17	.16	.56	26EpsSco, Zet2Sco, EtaSco, TheSco, Iot1Sco, KapSco, 35LamSco, Mu1Sco, 34UpsSco	Tail of Scorpius
32	.17	.17	1.0	21AlpSco, 20SigSco, 23TauSco	
33	.17	.09	.83	3AlpLyr, 10BetLyr, 14GamLyr, 12Del2Lyr, 6Zet1Lyr	Lyra
34	.16	.13	.01	21AlpAnd, 54AlpPeg, 53BetPeg, 88GamPeg	Square of Pegasus
35	.16	.08	.56	6Alp2Cap, 9BetCap, 40GamCap, 49DelCap, 34ZetCap, 23TheCap, 32IotCap, 16PsiCap, 18OmeCap	Capricornus
36	.16	.12	.35	21AlpSco, 8Bet1Sco, 7DelSco, 26EpsSco, EtaSco, TheSco, Iot1Sco, KapSco, 35LamSco, Mu1Sco, 6PiSco, 23TauSco	Scorpius

Note: Human scores roughly indicate how often an asterism was found in our data set, and weighted human scores were adjusted for the unequal representation of geographic regions within the data set. The model scores roughly indicate how well these asterisms were captured by the graph clustering model (1.0 indicates a perfect match). The star names are Bayer/Flamsteed designations drawn from Version 1.1 of the HYG database (Nash, n.d.): For example, 25EtaTau is the star Eta Tauri (Bayer), also known as 25 Tauri (Flamsteed).

the first of these failings more heavily than the second. This property is especially useful when comparing an asterism with a reference that includes a relatively large number of stars. For example, the teapot asterism includes eight of the brightest stars in Sagittarius, and the version of Sagittarius in our Western system includes 17 stars after those fainter than 4.5 in magnitude are removed. Intuitively, the teapot matches Sagittarius fairly well, and the function in Equation 1 assigns a match of .47 between the teapot (a) and Sagittarius (r). If we used an alternative match function where the numerator included penalties for both $|a \setminus r|$ and $|r \setminus a|$, then the match between the teapot and Sagittarius would be 0.

The match between asterism a and an entire system of asterisms S is defined as follows:

$$\text{match}(a, S) = \max_{r \in S}\big(\text{match}(a, r)\big). \tag{2}$$

Equation 2 captures the idea that a matches S well if there is at least one asterism r in S that matches a well. Finally, the human scores in Table 1 were calculated using the following formula:

$$\text{human}(a, \mathcal{S}_{\text{human}}) = \text{mean}_{S \in \mathcal{S}_{\text{human}}}\big(\text{match}(a, S)\big), \tag{3}$$

where $\mathcal{S}_{\text{human}}$ is the set of all 27 systems in our data set. We computed scores for all asterisms in the entire data set, but to avoid listing variants of the same basic asterism, we included an asterism a in Table 1 only if $\text{match}(a, r)$ was less than .5 for all asterisms r previously listed in the table. To establish a somewhat arbitrary threshold, we will say that an asterism recurs across cultures if it achieves a human score of .2 or greater. Of the 605 asterisms in our data set, 28% met this criterion, and these recurring asterisms are the subset most likely to be explained by principles of perceptual grouping.

Our data set is tilted toward cultures from the Northern Hemisphere and cultures with historical relationships to the Western system, and both factors may have distorted the human scores in Table 1. To adjust for this imbalance, we sorted the 27 cultures into six geographic regions: Asian, Australian, European, North American, Oceanic, and South American. We then computed weighted human scores for each asterism by replacing the mean in Equation 3 with a weighted mean that gives equal weight to each of the six geographic regions. Weighted human scores are included in Table 1, and these scores suggest that southern asterisms including the Southern Pointers and Corona Australis deserve to be listed alongside the 10 recurring asterisms singled out at the top of Figure 1a. Regardless of whether we considered human scores or weighted human scores, we found that convergences in asterisms across cultures go beyond the handful of prominent examples typically cited in the literature.

A Computational Model of the Grouping of Stars Into Asterisms

To explain shared patterns in the night sky, scholars from multiple disciplines have suggested that asterisms are shaped in part by universal perceptual principles, including the principles that bright objects are especially salient and that nearby objects are especially likely to be grouped (Hutchins, 2008; Metzger, 1936/2006; Yantis, 1992). Yantis (1992), for example, wrote that "certain stellar configurations are 'seen' by virtually all cultures (e.g., the Big Dipper)" and that "these constellations are universal in that they satisfy certain of the classic Gestalt laws of proximity, good continuation, similarity (in brightness), and Prägnanz" (p. 325). Claims that Gestalt principles account for star grouping across cultures are mostly anecdotal, but the principles themselves have been studied in detail by psychologists (Elder, 2015; Wagemans, Elder, et al., 2012; Wagemans, Feldman, et al., 2012) and have inspired the development of formal models of perceptual grouping (Compton & Logan, 1993; Dry et al., 2009; Froyen et al., 2015; Im et al., 2016; Kubovy et al., 1998; van den Berg, 1998). We built on this tradition by using a computational model (the graph clustering [GC] model) to explore the extent to which the factors of brightness and proximity account for asterisms across cultures.

The GC model constructs a graph with the stars as nodes, assigns strengths to the edges on the basis of proximity and brightness, and applies a threshold to the graph so that only the n strongest edges remain. Figure 1b shows the model graph when the threshold n is set to 320. The connected components of this thresholded graph are the asterisms formed by the model. There is a strong resemblance between these model asterisms and the consensus system in Figure 1a. The model picked out groups that correspond closely to the 10 frequently occurring asterisms highlighted in the insets shown in Figure 1a. Beyond these 10 asterisms, the model also picked out the Southern Pointers, the teapot in Sagittarius, the head of Draco, the head and stinger of Scorpius, Lyra, the sickle in Leo, the shaft of Aquila, and more. Table S3 in the Supplemental Material lists all groups found by the model and indicates which of them are similar to human asterisms attested in Table S2.

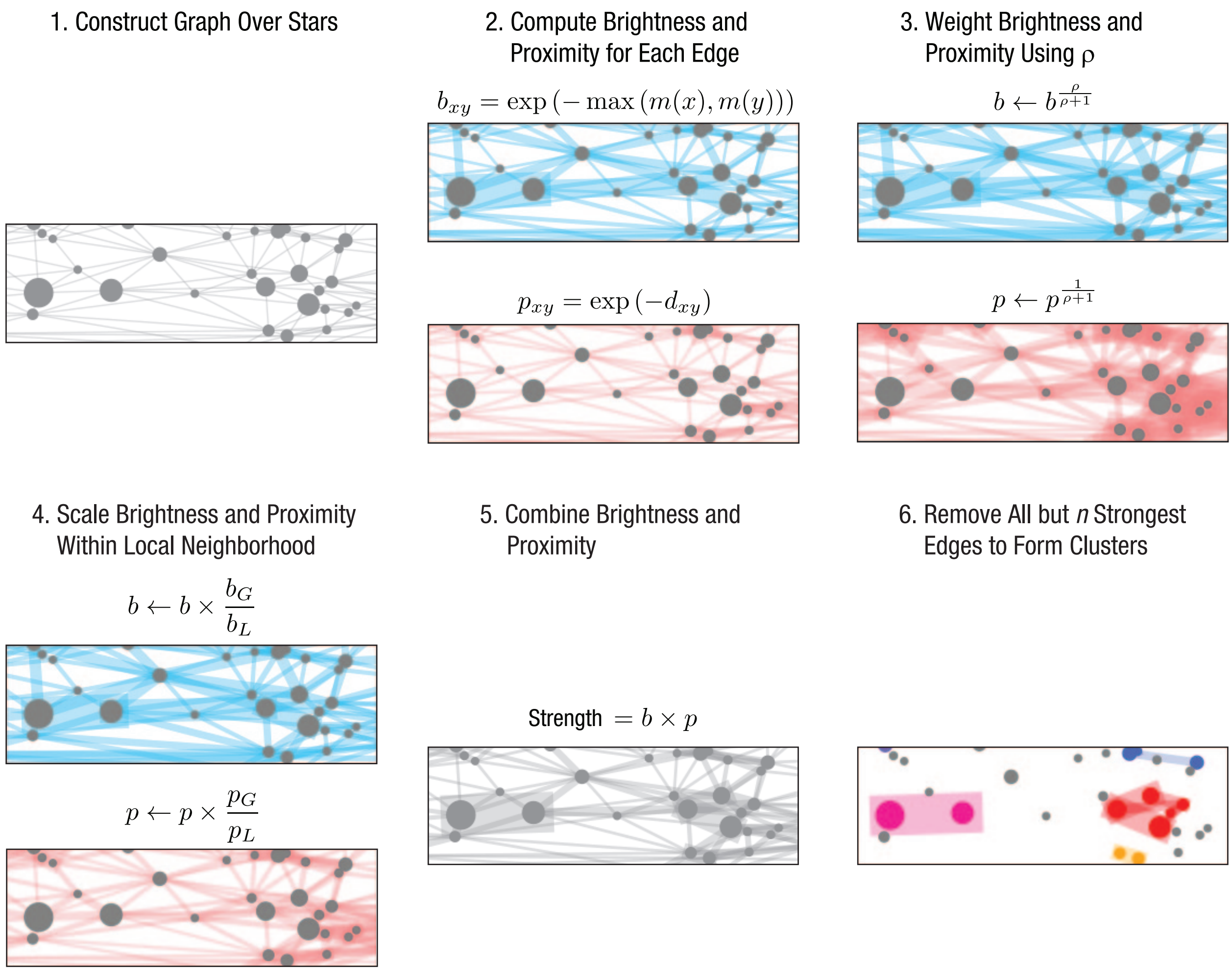

Fig. 2. Steps carried out by the graph clustering model. Each step is illustrated using a region of the sky that includes the Southern Cross and the Southern Pointers. The brightness weights (blue) and proximity weights (red) associated with the edge between x and y are denoted by b_{xy} and p_{xy}, respectively. The apparent magnitudes of stars x and y are denoted by $m(x)$ and $m(y)$, and d_{xy} is the angular separation between these stars. The median brightness weight across the entire graph is denoted by b_G, and the median brightness weight within 60° of a given edge is denoted by b_L. The proximity weights, p_G and p_L, are defined similarly. In Steps 2 through 6, edge widths are proportional to edge weights.

The steps that the model carries out are summarized in Figure 2. The first step is to construct a graph over stars. Existing graph-based clustering models typically operate over a graph corresponding to a minimal spanning tree (Zahn, 1971) or Delaunay triangulation (Ahuja, 1982; van den Berg, 1998), and the GC model uses the union of three Delaunay triangulations defined over stars with apparent magnitudes brighter than 3.5, 4.0, and 4.5. Delaunay-like representations are hypothesized to play a role in early stages of human visual processing (Dry et al., 2009), and combining Delaunay triangulations at multiple scales ensures that the resulting graph includes both edges between bright stars that are relatively distant and edges between fainter stars that are relatively close. The second step assigns a brightness and proximity to each edge. For an edge joining two stars, proximity is inversely related to the angular distance between the stars, and brightness is based on the apparent magnitude of the fainter of the two stars. The third step weights brightness and proximity using a parameter ρ. For all analyses, we set ρ to 3, which means that brightness was weighted more heavily than proximity. The fourth step scales brightness and proximity so that the distribution of these variables within a local neighborhood of 60° is comparable with the distribution across the entire celestial sphere. Scaling in this way allows the impact of brightness and proximity to depend on the local context. For example, the Southern Cross lies in a region that contains many stars in close proximity, and we propose that stars need to be especially close to stand out in this context. Previous psychological models of perceptual grouping incorporate analogous local scaling steps (Compton & Logan, 1993; van den Berg, 1998), and the neighborhood size of 60° was chosen to match the extent of midperipheral vision. The fifth step multiplies brightness and proximity to assign an overall strength to each edge, and the final step applies a threshold to the graph so that only the strongest n edges remain.

We compared the GC model with several alternatives, including variants that lack one of its components and variants that rely on either collinearity or good continuation in addition to brightness and proximity. We also evaluated a pair of models that rely on k-means clustering, and we assessed the CODE model of perceptual grouping (Compton & Logan, 1993). The results revealed that the GC model performed better than all of these alternatives (full details are provided in the Supplemental Material). Although adding good continuation to the model did not improve its performance, future work may be able to improve on our efforts in this direction. For example, the current model combines Corona Borealis with an extraneous star and does not connect the tail of Scorpius into a single arc, and finding the right way to incorporate good continuation may resolve both shortcomings.

Each human asterism can be assigned a score between 0 and 1 that measures how well it is captured by the GC model. For this purpose, we created a set $\mathcal{S}_{\mathrm{GC}}$ that includes model systems for all values of the threshold parameter n between 1 and 2,000. The model score for each human asterism a is defined as follows:

$$\text{model score}(a, \mathcal{S}_{\mathrm{GC}}) = \max_{S \in \mathcal{S}_{\mathrm{GC}}} \big(\text{match}(a, S)\big), \qquad (4)$$

which is 1 if a belongs to some system in $\mathcal{S}_{\mathrm{GC}}$. This approach makes it possible for nested asterisms (e.g., Orion's Belt and Orion) to be captured by the model, even though a single setting of n could capture at most one of these asterisms. Model scores are included in Table 1, and we will say that an asterism was captured by the model if it achieved a score of .2 or higher. By this criterion, 98% of the asterisms that recur across cultures and 80% of the entire data set were captured by the model.

Distributions of model scores for each culture in our data set are plotted in Figure 3. The model accounts for some cultures well—for example, 13 of 20 Arabic asterisms, 19 of 38 Marshall Islands asterisms, and 55 of 161 Chinese asterisms were captured perfectly by the model. The systems captured well by the model were drawn from a diverse set of geographical regions, suggesting that genealogical relationships between cultures are not enough to explain the recurring patterns captured by the model. Yet there are also many asterisms that were not captured by the model, and the Chinese and Western systems in particular include many asterisms with a model score of 0. Both systems partition virtually all of the visible sky into asterisms, and achieving this kind of comprehensive coverage may require introducing asterisms (including Herschel's "innumerable snakes") that do not correspond to natural perceptual units.

Although some attested asterisms missed by the GC model will probably resist explanation by any model of perceptual grouping, others can perhaps be captured by extensions of the model. For example, the model tended not to group stars separated by a relatively large distance. As a result, it missed the lower arm of the Northern Cross (Cygnus) and missed the Great Square of Pegasus entirely. These errors could perhaps be addressed by developing a multiscale approach that forms groups at different levels of spatial resolution (Estrada & Elder, 2006; Froyen et al., 2015). Another possible extension is to incorporate additional grouping cues such as symmetry and parallelism, which are known to influence human judgments (Feldman, 2007; Machilsen et al., 2009) and have been explored in previous computational work (Jacobs, 2003; Stahl & Wang, 2008).

In addition to scoring each system in our data relative to the GC model, we also examined how closely each system resembles other systems in our data set (see Fig. S13 in the Supplemental Material). The system most different from all others is the Chinese system, which includes more than 300 asterisms, many of which are small and have no counterparts in records for other cultures. In future work, the model may prove useful for evaluating hypotheses about historical relationships between systems from different cultures (Berezkin, 2005; Gibbon, 1964). For example, the model could be used to ask whether Oceanic constellations are more similar to Eurasian constellations than would be expected on the basis of perceptual grouping alone.

Discussion

For around a century, constellations have been informally used by Gestalt psychologists and their successors to illustrate basic principles of perceptual grouping (Köhler, 1929; Metzger, 1936/2006). To our knowledge, however, our work is the first to systematically explore the extent to which perceptual grouping can account for constellations across cultures. We began by asking which asterisms appear frequently across cultures, and our data suggest that lesser known asterisms such as

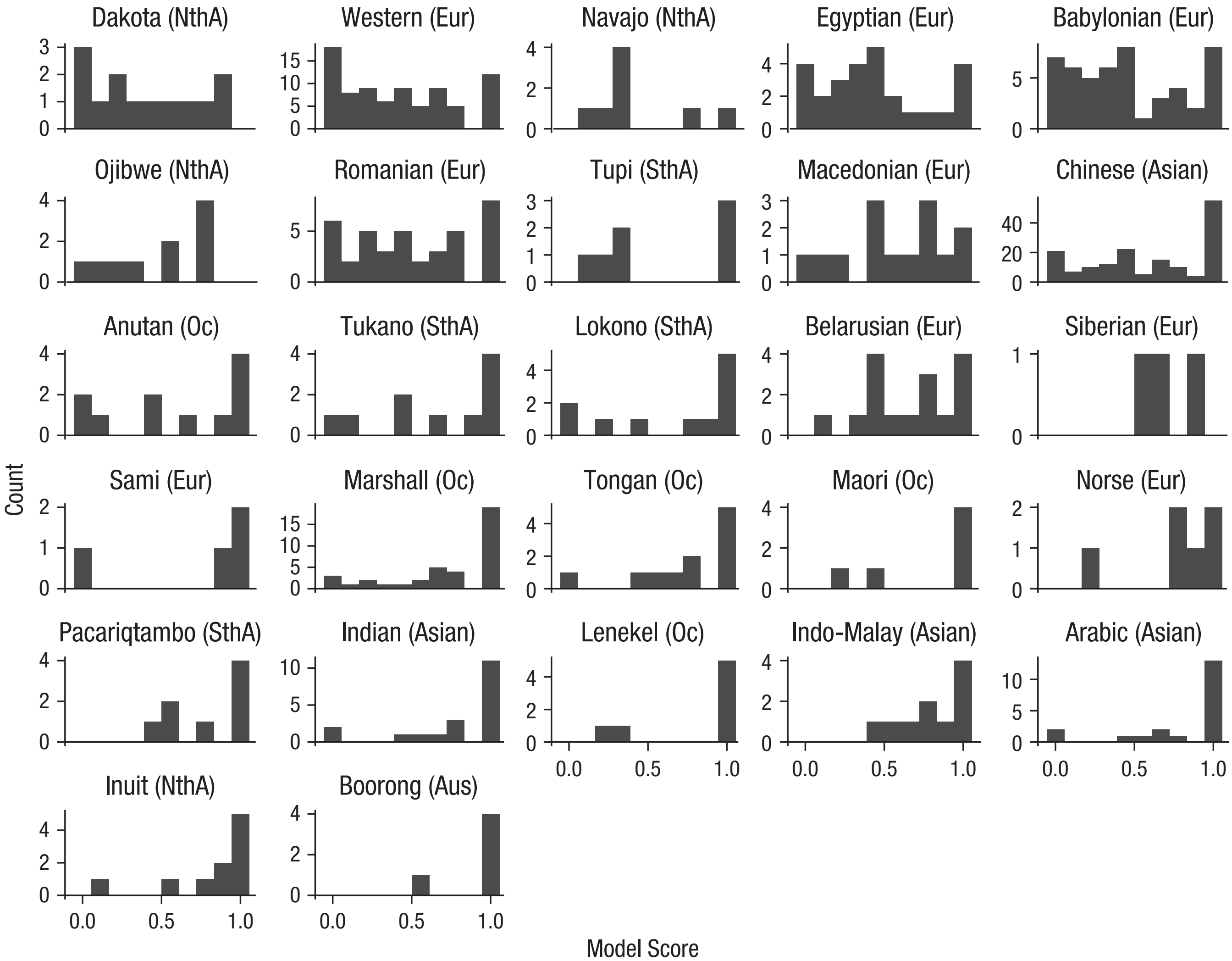

Fig. 3. Model results for individual cultures in our data set. Model scores of 1 indicate asterisms that are perfectly captured by the graph clustering model for some value of the threshold n, and each distribution includes scores for all asterisms that remain after filtering at a stellar magnitude of 4.5. The cultures are ordered on the basis of the means of the distributions, and the labels in parentheses indicate the geographic region used to compute the weighted scores in Table 1: Asian, Australian (Aus), European (Eur), North American (NthA), Oceanic (Oc), South American (SthA).

Delphinus and the head of Aries should be included alongside more familiar asterisms such as the Pleiades and the Big Dipper. We then presented a computational analysis that suggests that perceptual grouping based on brightness and proximity is enough to account for many of the asterisms that recur across cultures. Previous discussions of convergence in asterisms across cultures have typically focused on a handful of familiar examples including the Pleiades and the Big Dipper, but our work suggests that similarities in asterisms across cultures go deeper than previously recognized.

Our computational model was developed to explain how the night sky is clustered into groups of stars, but it did not address how the stars in each group are organized into figures. Our approach therefore complements the approach of Dry et al. (2009), who focused on the organization of star groups into figures but did not explain how these star groups might initially have been picked out of the full night sky. Both of these approaches use a Delaunay triangulation to capture proximity relationships between stars, and future work may be able to combine them into a single computational model that both picks out groups of stars and organizes them into figures.

We focused throughout on similarities in star groups across cultures, but there are also striking similarities in the names and stories associated with these groups (Baity et al., 1973; Culver, 2008; Gibbon, 1964). For example, in Greek traditions, Orion is known as a hunter pursuing the seven sisters of the Pleiades, and versions of the same narrative are shared by multiple Aboriginal cultures of Australia (Johnson, 2011; Leaman & Hamacher, 2019). Our work suggests that perceptual grouping helps to explain which patterns of stars are singled out for attention, but understanding the meanings invested in these asterisms requires a deeper knowledge of history, cognition, and culture.

Transparency

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Author Contributions
C. Kemp and D. W. Hamacher compiled the data, and C. Kemp implemented the models and analyses and wrote the manuscript. All the authors discussed the models and analyses, commented on the manuscript, and approved the final manuscript for submission.
Declaration of Conflicting Interests
The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.
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Open Practices
All data and analysis code have been made publicly available via Zenodo and can be accessed at https://doi.org/10.5281/zenodo.6015645. The design and analysis plan for the study were not preregistered. This article has received the badges for Open Data and Open Materials. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/09567976211044157

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