40 Outlier

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> "Outlier": Statistics. An observation whose value lies outside the set of values considered likely according to some hypothesis (usually one based on other observations); an isolated point.
>
> —*Oxford English Dictionary* 2017

> Communities . . . come into being not through the recognition, generation, or establishment of universal, neutral laws and conventions that bind and enforce them, but through the remainders they cast out, the figures they reject, the terms that they consider unassimilable, that they attempt to sacrifice, revile and expel.
>
> —Grosz 2001

In statistics, an outlier is a data point that does not conform to the rest. When plotted on a chart or a graph, it lies outside the pattern displayed by the rest of the data. It is "very different to the other observations in a set of data" (Doyle 2016, 256). The outlier is "an isolated point" (*Oxford English Dictionary* 2017). Outlier values "do not agree with the pattern of the majority of other values" (Holloway and Nwaoha 2012, 391), and extensive statistical literature discusses when one may reasonably reject outlier values while undertaking a data analysis or mitigate their influence by weighting them differently. But there is often uncertainty as to whether an outlier is an error in the recording of data or represents a true variation in the population. Since rejecting outliers may come at the risk of excluding valid observations, the best-practice guidance for dealing with outliers is to "inspect the data as it is collected during the experiment, identify discrepant values, and determine their cause" (Holloway and Nwaoha 2012, 391).

This chapter represents exactly such a practical and ethical inspection of outliers in relation to gender data, computation, and big data sets. From my standpoint as a software developer and scholar, a data-driven approach to gender has a great deal of potential for exposing the structural and systemic forces of inequality operating in society. As feminist geographer

Joni Seager says, “What gets counted counts” (D’Ignazio and Klein~~,~~ 2020). But counting comes with caveats, particularly in relation to categorizing people and making them visible to powerful institutions. Here I draw on feminist theory to understand that categories of gender identity are not intrinsic, natural, or biological distinctions between people and groups but rather are social, cultural, and political distinctions based on the way power is allocated and wielded unevenly across a population (Butler 1990; Fausto-Sterling 2008).

Gender data are often more complicated than they appear on the surface. The received wisdom is that two categories exist: the world is made up of men and women. And yet the historical record shows that there have always been more variations in gender identity than Western society has cared to outwardly acknowledge or collectively remember. These third, fourth, and nth genders go by different names in the different historical and cultural circumstances in which they originate, including *transgender people* (Williams 2014), *female husbands* (Weeks 2015), *hijras* (Sharma 2012), *two-spirit people* (Driskill 2011), *pansy performers* (Chauncey 1994), *mahu* (Mock 2014), and *sworn virgins* (Zumbrun 2007). This chapter argues that while nonbinary genders represent outliers in terms of population ratio, they also represent an expected variation in the population—which is to say that there have always been and will always be more than two genders. While most current computational applications ignore and exclude nonbinary gender data (if they consider gender at all), a theoretical framework informed by intersectional feminism and transfeminism offers an opportunity to deal with gender data more appropriately and ethically.

Broadly speaking, feminist theory uses the fact of unequal gender relations to challenge concepts such as neutrality and objectivity precisely because of the alternative perspectives that they exclude (notably, women’s and nonbinary people’s). Intersectional feminism, created and elaborated by Black feminists and women of color in response to the exclusions of white feminism, roots its analysis in the overlapping dimensions, such as race, class, and ability, of any examination of unequal power relations (Combahee River Collective 1978; Crenshaw 1990). Transfeminism links feminist theory to transgender oppression and activism (Erickson-Schroth 2014). There are increasing attempts in human-computer interaction (HCI) and design to mobilize intersectional feminist approaches to computation that serve justice-oriented goals. The Design Justice Network asks designers to sign up to ten principles, including the idea that design should “sustain, heal and empower our communities” (Costanza-Chock~~, forthcoming).~~ Feminist HCI starts by centering the perspectives of those who are marginalized and excluded “so as to expose the unexamined assumptions of dominant epistemological paradigms, avoid distorted or one-sided accounts of social life, and generate new and critical questions” (Bardzell 2010, 1302). From a gender identity standpoint, this would involve centering women’s and nonbinary people’s viewpoints as a way of understanding why society (and its software systems) is so invested in maintaining and policing the gender binary (for an example, see Currah and Mulqueen [2011] on traveling while trans). In *Data Feminism* (2020), Lauren F. Klein and I assert that using data and computation for coliberation requires challenging the gender binary.

The term *gender datafication* can be used to refer to the external digital classification of gender and its representation in databases and code (Bivens and Haimson 2016). But how we choose to datafy gender can have profound consequences. The majority of people are *cisgender*, meaning that their gender identity aligns with their assigned sex. They are assigned female at birth and identify as a woman or assigned male at birth and identify as a man. While assigned sex, gender identity, and gender expression are aligned for cis people, they are not aligned for people who identify as transgender, genderqueer, and/or gender nonconforming (GNC). *Nonbinary gender* is an umbrella category for people who do not identify as men or women.

Researchers at the Williams Institute at the University of California, Los Angeles, estimate that 0.6 percent of the US population is transgender (Flores et al. 2016) and 3.5 percent is not straight in sexual orientation (Gates 2014). This means that the vast majority—99.4 percent—of people are cisgender, and 96.5 percent are straight. However, when you scale the numbers at the size of the country's population, those who are not cisgender and heterosexual amount to nine million individuals, about the population of the state of New Jersey. At scale, then, a computational system that only classifies gender along a binary, or makes assumptions about heterosexuality, will be missing critical information for a significant portion of the population. Thus, what appears to be a categorical outlier in any smaller data set should in fact be considered an expected outcome of measuring gender and/or sexuality in the population.

Yet big data and artificial intelligence research that deals with gender has almost invariably treated it as a binary. Competitions on Kaggle.com, a popular web platform for predictive modeling and analytics, have sought to predict gender from fingerprints and handwriting. Other work has sought to automatically identify the gender of bloggers (Belbachir, Henni, and Zaoui 2013), novelists (Koppel, Argamon, and Shimoni 2002), movie reviewers (Otterbacher 2013), and Twitter users (Kokkos and Tzouramanis 2014) based on the style of their language. There are multiple libraries for predicting the gender of people based on their name, such as OpenGenderTracker, the R gender package, and the controversially named "sex machine" Ruby Gem (now called Gender_Detector; Muller 2014). Nathan Matias (2014) gives a comprehensive account of more of this research, including different uses, methodological choices, and ethical guidelines. In 2018, HCI researcher Os Keyes (2018) evaluated fifty-eight technical papers about automatic gender recognition (detecting gender by analyzing images of people's faces) and found that 95 percent of papers treated gender as a binary (see also Keyes, chapter 35, this volume).

Consumer-oriented platforms, responding to user pressure, have slowly begun to recognize more than two genders. Sort of. In 2014, Facebook expanded its gender options from two to fifty-eight for English speakers in the US and UK. The gender options it added were created in consultation with the LGBTQ+ community and ranged from "GNC" to "two-spirit" to "trans female." The corporation later added the abilities to identify as more than one gender and to input a custom gender. Other social networking and dating sites have followed suit. For example, OKCupid provides more than twenty genders and thirteen sexual orientations for users to choose from. While these changes may appear to be progressive, Facebook's databases continued for several years to resolve custom and nonbinary genders into "male" and "female" on the back end, based on the binary gender that users select at sign-up, where the custom option is not available (Bivens 2015). As recently as 2015, the Facebook Marketing API resolved gender to 1 = male, 2 = female. So while a user and their friends may have seen them presented as the gender they selected, they were a 1 = male or 2 = female to any advertisers looking to purchase their attention. This reinforces Bivens's (2015) point that changes at the level of the interface are mere marketing, and platforms do not actually have an interest in "deprogramming" the gender binary.

While these platforms and applications seek to generalize about majority populations who largely do fall within the binary categories of male and female, they reinforce the idea that the world is made up of *only* these two groups, which is categorically, historically, and empirically untrue. Moreover, gender detection applications erroneously assume that gender identity is a natural, essential property of a person that can be detected by an outside observer—that is, that it can be reduced to the curvature of one's handwriting, the length of one's hair, or the shape of one's face. Finally, these works tend to codify (literally, to write into code) essentialist, stereotypical characterizations of male and female communication patterns and present them as universal, context-free, scientific truths. For example: "Women tend to express themselves with a more emotional language"; "men are more proactive, directing communication at solving problems, while women are more reactive" (Kokkos and Tzouramanis 2014). As we know from disciplines such as media studies, geography, and science and technology studies, representations do not innocently reflect reality but also have a role in producing it. This applies to code and statistical modeling just as it does to television shows, movies, images, and visualizations. Bivens and Haimson (2016) have argued that digital representations of gender on social media platforms have a strong influence on categories of gender in wider society. Ignoring and excluding the lived experiences of trans and nonbinary people, especially in data and statistics—forms of representation perceived to be comprehensive and systematic—reinforces their societal erasure. As Keyes states: "This erasure is a foundational component of the discrimination trans people face" (Keyes 2018, 3).

Official, state-sanctioned acknowledgments and rights for people who are minoritized for their gender identity have been expanding in Western democracies and the global South over the past fifty years. Nations around the world provide varied and uneven abilities for individuals to officially amend their sex marker on official documents. Some, such as Japan, mandate hormone therapy, surgery, and sterilization before one can be legally recognized as another gender. As of 2017, only five countries allowed individuals to determine their own gender: Ireland, Denmark, Norway, Greece, and Malta. Iran is the global capital of sex reassignment surgery (Tower 2016). Amnesty International (2017) advocates for LGBTQ+ rights as basic human rights. At least three countries—Australia, Nepal, and India—have included third gender options in their censuses. The state of California now recognizes three genders on state identification documents: nonbinary, female, and male. But in practice, GNC people face harassment, discrimination, and violence, even in the most legally progressive places, despite the fact that they represent a significant subpopulation (Albert 2019; Bettcher 2014).

Trans and GNC people will represent statistical outliers in small data sets and numerical minorities in almost any data set that collects gender at the scale of the population, just as Native Americans will represent a small proportion of any US-based data set that collects race and ethnicity. As Brooke Foucault Welles states: "When women and minorities are excluded as subjects of basic social science research, there is a tendency to identify majority experiences as 'normal,' and discuss minority experiences in terms of how they deviate from those norms" (Foucault Welles 2014). Indeed, transgender studies traces the relatively recent rise of the idea of "the normal" through both the statistical and sociopolitical meanings of the term (Stephens 2014) and demonstrates how "normalization" is used to justify administrative violence against those that fall outside of the category (Spade and Rohlfs 2016). Minority experiences are typically relegated to the margins of analysis or, as mostly happens with nonbinary people in relation to computation and gender, excluded altogether. This has dubious ethical and empirical implications and has even been called "demographic malpractice" by researchers at the Williams Institute (Chalabi 2014). Instead, Foucault Welles proposes that data scientists use the experiences of minoritized groups as reference categories in themselves. This means not just collecting more than two genders but also disaggregating any data processing, data analysis, and results based on these categories.

Here there is an opportunity to go even further and engage in an equity-focused approach: instead of creating data sets that represent minoritized genders according to their occurrence in the population, we can create data sets where they are the majority. Whether a data point (or a person who has been datafied) constitutes an outlier is contextual—dependent on which other data (or people) have been selected for comparison. It has to do with whose identities are centered and whose are relegated to the margins. Feminist HCI centers the people at the margins in order to challenge the ongoing dominance of those at the center.

At the same time, it is important to work with GNC people to understand whether they want to have their data included in any particular system. Research by Hamidi and coauthors (2018) found that transgender users had overwhelmingly negative attitudes toward automated gender recognition technology. Depending on what data are being collected and whether such data are personally identifiable (or easily deanonymized), it is also important to recognize the potential risk of stating one's gender as something other than male or female. If the data set aspires to be representative of a geographically bounded population, for example, the number of nonbinary people may be small enough to identify these individuals, even within otherwise large data sets. Even when individuals do not volunteer gender identity information to an application, it may be possible to attempt to algorithmically infer their gender identity or sexual orientation from their social networks (Jernigan and Mistree 2009). This can pose risks of repercussion in the form of either personal shame for people who have hidden their gender identity or discrimination, violence, and imprisonment, depending on the context and community where they live. These potential harms have led scholars to argue that computational systems should be designed to support obscurity and invisibility, key safety strategies for trans, nonbinary, and other marginalized users (Haimson and Hoffman 2016).

It can also be challenging to collect information about nonbinary genders. How many and which other genders exist in a society depends heavily on culture and context. For example, the government of Nepal attempted to add to its census the category of "third gender," but nonbinary gender communities, more likely to consider themselves *kothi* or *methi*, did not identify with this term (Park 2016). The Williams Institute and the Human Rights Campaign provide short guides for collecting inclusive gender data (HRC 2019; Park 2016). But just changing the user interface (providing more choices in a drop-down menu, or a write-in option, or the ability to choose multiple options) is not always the best path. Depending on the circumstances, the most ethical thing to do might be to avoid collecting gender data, make gender optional, or even stick with binary gender categories. For example, communications scholar Nikki Usher and her coauthors (2018) undertook a large-scale analysis of political journalists' gendered communication patterns on Twitter. Their study stuck with binary categories because, as they state, "if you are trying to make a point that the gender binary, which is so strong and endemic, shapes and structures all sorts of inequality—then the binary has to be the point of analysis because you're trying to show the problem as it is manifest in the dominant interpretation of reality, not the counterhegemonic one we wish were more pervasive and accepted" (Usher, ~~email to Catherine D'Ignazio,~~ August 9, 2019). Moreover, if gender data are going to be used in processes with known structural inequalities, such as hiring and promotion, the most ethical action might be to entirely obscure a person's gender from both the human decision-makers and the algorithms making discriminatory decisions, in order to avoid bias (Datta, Tschantz, and Datta 2015; Goldin and Rouse 2000).

Finally, even if there is low risk of personal harm in collecting gender data, cisgender institutions can still use ~~that~~ data in ways that cause group harm, such as perpetuating deficit narratives and pathologizing trans and nonbinary people. For example, while it is true that there are high rates of suicide among transgender youth, insensitive accounts of these statistics can inadvertently paint youth as passive victims in need of saving by cisgender adults. This points to the crucial importance of involving nonbinary people at every stage of the process in a gender data project, from data collection to analysis to communication.

So where do we land in relation to gender datafication and outliers? Outliers are not rejected and ignored in all computing contexts. In fact, outlier detection is a lively subfield of computer science and statistics. It has many applications, ranging from detecting fraud to identifying land mines to noting failures in aircraft engines. Outlier detection can also help identify intruders in security systems and focus on "bursts" in information systems, such as when a hashtag goes viral in a breaking news situation (Hodge and Austin 2004). From a technical standpoint, outlier detection for the purposes of preventing human harm and safeguarding financial investments is thriving. But it is important to recognize that values are always embedded in these applications and models. The decision to invest resources in detecting credit card fraud from a sea of otherwise unobjectionable transactions is made based on values that prioritize profit for a corporation. What if, instead or in addition, we prioritized safety and inclusion for women and GNC communities?

For those computational applications that deal with gender data: What might they look like if they *de-outliered* nonbinary people's data? This would involve disaggregating and centering the experiences of nonbinary people, as in Starks, Dillahunt, and Haimson's (2019) exploratory study about transgender and nonbinary digital practices of safety. What might these applications look like if they were designed by and with trans and nonbinary people, as in Ahmed's (2019) proposal for a trans voice-training application? What other outliers might we be systematically missing, excluding, suppressing, and willfully ignoring, and what does that tell us about ourselves? Gender data represent complicated terrain for computational applications, for numerous reasons outlined here. But there is an ethical and empirical imperative to tackle this complexity. The world is not and has never been populated by only two genders. To assume gender is a simple binary is simply empirically wrong.

Note

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References

Ahmed, Alex A. 2019. "Bridging social critique and design: Building a health informatics tool for transgender voice." In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, DC02:1–DC02:4. New York: Association for Computing Machinery.

Albert, Kendra. 2019. "Their law." *Harvard Law Review Blog*, June 26, 2019. https://blog.harvardlawreview.org/their-law/.

Amnesty International. 2017. "The state of LGBT human rights worldwide." Amnesty International. Accessed August 30, 2019. https://www.amnestyusa.org/the-state-of-lgbt-rights-worldwide/.

Bardzell, Shaowen. 2010. "Feminist HCI: Taking stock and outlining an agenda for design." In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1301–1310. New York: Association for Computing Machinery. https://doi.org/10.1145/1753326.1753521.

Belbachir, Faiza, Khadidja Henni, and Lynda Zaoui. 2013. "Automatic detection of gender on the blogs." In *2013 ACS International Conference on Computer Systems and Applications (AICCSA)*, edited by IEEE, 1–4. Piscataway: IEEE. https://doi.org/10.1109/AICCSA.2013.6616510.

Bettcher, Talia Mae. 2014. "Transphobia." *Transgender Studies Quarterly* 1 (1–2): 249–251.

Bivens, Rena. 2015. "The gender binary will not be deprogrammed: Ten years of coding gender on Facebook." *New Media and Society* 19 (6). https://doi.org/10.1177/1461444815621527.

Bivens, Rena, and Oliver L. Haimson. 2016. "Baking gender into social media design: How platforms shape categories for users and advertisers." *Social Media + Society* 2 (4). https://doi.org/10.1177/2056305116672486.

Butler, Judith. 1990. *Gender Trouble: Feminism and the Subversion of Identity*. New York: Routledge.

Chalabi, Mona. 2014. "Why we don't know the size of the transgender population." *FiveThirtyEight*. https://fivethirtyeight.com/features/why-we-dont-know-the-size-of-the-transgender-population/.

Chauncey, George. 1994. *Gay New York: Gender, Urban Culture, and the Makings of the Gay Male World, 1890–1940*. New York: Basic Books.

Combahee River Collective. 1978. "The Combahee River Collective statement." Circuitous.org. Accessed April 3, 2019. http://circuitous.org/scraps/combahee.html.

Costanza-Chock, Sasha. ~~Forthcoming.~~ *Design Justice*. Cambridge, MA: MIT Press.

Crenshaw, Kimberlé. 1990. "Mapping the margins: Intersectionality, identity politics, and violence against women of color." *Stanford Law Review* 43:1241–1299.

Currah, Paisley, and Tara Mulqueen. 2011. "Securitizing gender: Identity, biometrics, and transgender bodies at the airport." *Social Research: An International Quarterly* 78 (2): 557–582.

Datta, Amit, Michael Carl Tschantz, and Anupam Datta. 2015. "Automated experiments on ad privacy settings." *Proceedings on Privacy Enhancing Technologies* 1:92–112. https://doi.org/10.1515/popets-2015-0007.

D'Ignazio, Catherine, and Lauren F. Klein. 2020. *Data Feminism*. Cambridge, MA: MIT Press.

Doyle, Charles, ed. 2016. *A Dictionary of Marketing*. Oxford: Oxford. University Press. https://doi.org/10.1093/acref/9780198736424.001.0001.

Driskill, Qwo-Li, ed. 2011. *Queer Indigenous Studies: Critical Interventions in Theory, Politics, and Literature*. Tucson: University of Arizona Press.

Erickson-Schroth, Laura, ed. 2014. *Trans Bodies, Trans Selves: A Resource for the Transgender Community*. Oxford: Oxford University Press.

Fausto-Sterling, Anne. 2008. *Sexing the Body: Gender Politics and the Construction of Sexuality*. New York: Basic Books.

Flores, Andrew R., Jody L. Herman, Gary J. Gates, and Taylor N. T. Brown. 2016. *How Many Adults Identify as Transgender in the United States?* Los Angeles: Williams Institute. https://williamsinstitute.law.ucla.edu/wp-content/uploads/How-Many-Adults-Identify-as-Transgender-in-the-United-States.pdf.

Foucault Welles, Brooke. 2014. "On minorities and outliers: The case for making big data small." *Big Data and Society* 1 (1). https://doi.org/10.1177/2053951714540613.

Gates, Gary J. 2014. *LGBT Demographics: Comparisons among Population-Based Surveys: Executive Summary*. Los Angeles: Williams Institute. https://williamsinstitute.law.ucla.edu/wp-content/uploads/lgbt-demogs-sep-2014.pdf.

Goldin, Claudia, and Cecilia Rouse. 2000. "Orchestrating impartiality: The impact of 'blind' auditions on female musicians." *American Economic Review* 90 (4): 715–741. https://doi.org/10.1257/aer.90.4.715.

Grosz, Elizabeth A. 2001. *Architecture from the Outside: Essays on Virtual and Real Space*. Cambridge, MA: MIT Press.

Haimson, Oliver L., and Anna Lauren Hoffmann. 2016. "Constructing and enforcing 'authentic' identity online: Facebook, real names, and non-normative identities." *First Monday* 21 (6). https://doi.org/10.5210/fm.v21i6.6791.

Hamidi, Foad, Morgan Klaus Scheuerman, and Stacy M. Branham. 2018. "Gender recognition or gender reductionism?: The social implications of embedded gender recognition systems." In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 8. New York: Association for Computing Machinery.

Hodge, Victoria J., and Jim Austin. 2004. "A survey of outlier detection methodologies." *Artificial Intelligence Review* 22;85–126.

Holloway, Michael D., and Chikezie Nwaoha. 2012. *Dictionary of Industrial Terms*. Beverly, MA: Scrivener.

HRC (Human Rights Campaign). 2019. "Collecting transgender-inclusive gender data in workplace and other surveys." *Human Rights Campaign*. Accessed August 30, 2019. https://www.hrc.org/resources/collecting-transgender-inclusive-gender-data-in-workplace-and-other-surveys.

Jernigan, Carter, and Behram F. T. Mistree. 2009. "Gaydar: Facebook friendships expose sexual orientation." *First Monday* 14 (10). https://doi.org/10.5210/fm.v14i10.2611.

Keyes, Os. 2018. "The misgendering machines: Trans/HCI implications of automatic gender recognition." *Proceedings of the ACM on Human-Computer Interaction* 2;1–22.

Kokkos, Athanasios, and Theodoros Tzouramanis. 2014. "A robust gender inference model for online social networks and its application to LinkedIn and Twitter." *First Monday* 19 (9). https://doi.org/10.5210/fm.v19i9.5216.

Koppel, ~~M.,~~ Shlomo Argamon, and Anat Rachel Shimoni. 2002. "Automatically categorizing written texts by author gender." *Literary and Linguistic Computing* 17 (4): 401–412. https://doi.org/10.1093/llc/17.4.401.

Matias, Nathan. 2014. "How to identify gender in datasets at large scales, ethically and responsibly." *MIT Center for Civic Media* (blog). October 22, 2014. https://civic.mit.edu/blog/natematias/best-practices-for-ethical-gender-research-at-very-large-scales.

Mock, Janet. 2014. *Redefining Realness: My Path to Womanhood, Identity, Love and So Much More*. New York: Atria Books.

Muller, Brian. 2014. "Why I'm renaming a gem." *Finding Science*, November 17, 2014. http://findingscience.com/ruby/2014/11/17/why-im-renaming-a-gem.html.

Otterbacher, Jahna. 2013. "Gender, writing and ranking in review forums: A case study of the IMDb." *Knowledge and Information Systems* 35 (3): 645–664. https://doi.org/10.1007/s10115-012-0548-z.

Oxford English Dictionary. 2017. "Outlier." Accessed August 30, 2019. http://www.oed.com/view/Entry/133735?redirectedFrom=outlier.

Park, Andrew. 2016. *Reachable: Data Collection Methods for Sexual Orientation and Gender Identity*. Los Angeles: Williams Institute.

Sharma, Preeti. 2012. "Historical background and legal status of third gender in Indian society." *International Journal of Research in Economics and Social Sciences* 2 (12): 64–71.

Spade, Dean, and Rori Rohlfs. 2016. "Legal equality, gay numbers and the (after?) math of eugenics." *Scholar and Feminist Online* 13 (2). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2872953.

Starks, Denny L., Tawanna Dillahunt, and Oliver L. Haimson. 2019. "Designing technology to support safety for transgender women and non-binary people of color." In *Companion Publication of the 2019 Designing Interactive Systems Conference*, 289–294.

Stephens, Elizabeth. 2014. "Normal." *Transgender Studies Quarterly* 1 (1–2): 141–145.

Tower, Kimberly. 2016. "Third gender and the third world: Tracing social and legal acceptance of the transgender community in developing countries." *Concept* 39:1–21.

Usher, Nikki, Jesse Holcomb, and Justin Littman. 2018. "Twitter makes it worse: Political journalists, gendered echo chambers, and the amplification of gender bias." *International Journal of Press/Politics* 23 (3): 324–344.

Weeks, Linton. 2015. "'Female husbands' in the 19th century." *NPR*, January 29, 2015. https://www.npr.org/sections/npr-history-dept/2015/01/29/382230187/-female-husbands-in-the-19th-century.

Williams, Cristan. 2014. "Transgender." *Transgender Studies Quarterly* 1 (1–2): 232–234.

Zumbrun, Joshua. 2007. "The sacrifices of Albania's 'sworn virgins.'" *Washington Post*, August 11, 2007. http://www.washingtonpost.com/wp-dyn/content/article/2007/08/10/AR2007081002158.html.