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THE DILEMMA OF FALSE POSITIVES: MAKING CONTENT ID ALGORITHMS MORE CONDUCTIVE TO FOSTERING INNOVATIVE FAIR USE IN MUSIC CREATION

Toni Lester*
Dessislava Pachamanova**

ABSTRACT

Content ID programs commonly use algorithms to block uploaded music when the algorithm concludes the owners of certain copyrighted works will claim their work is being used without consent. However, algorithmic enforcement programs can produce “false positives,” where legally allowable music associated with a reference file is inappropriately blocked. The phenomenon of false positives is especially problematic for songwriters, composers, experimental music artists and others who create music by combining their own vocal or instrumental performance with work created by others and “loops” from audio libraries. Balanced by such factors as how much a new work damages the market for a prior work and how much of a prior work is used in a new work, the “fair use” defense allows songwriters to upload technically infringing work if the new work amounts to a critique, is in the public domain, or sufficiently transforms the original work to render it new. This article explains how Content ID algorithms are developed and interpreted and discusses how the fair use defense can sometimes limit the extent to which Content ID programs can block innovative music creation. The article offers methods for defining and measuring algorithmic effectiveness that both account for the risk of false positives and protect the proprietary interests of copyright holders. It also proposes a new regulatory scheme that ensures these methods are implemented properly. The proposed regulatory scheme should lead to a more equitable system for music creators and original copyright holders and to more inventive and interesting music for fans.

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INTRODUCTION

Musician John Boydston recently resolved a dispute with music distributor Rumblefish that arose after YouTube’s Content ID system incorrectly identified Boydston’s original work as infringing.¹ Boydston is not alone. Many songwriters are complaining about YouTube’s Content ID program, which uses algorithms to block uploaded music when the algorithm concludes the owners of certain copyrighted works will claim their work is being used without consent.² Large music publishers like Universal Music Corporation zealously

¹ Mike Masnick, *How Rumblefish Ended Up Claiming Copyright On A Song Uploaded By The Band Who Actually Held The Copyright*, TECH DIRT (April 25, 2012, 12:35pm), www.techdirt.com/articles/20120425/00115218642/how-rumblefish-ended-up-claiming-copyright-song-uploaded-band-who-actually-held-copyright.shtml.

² Taylor B. Bartholomew, Note, *The Death of Fair Use in Cyberspace: YouTube and the*

require YouTube to issue take-down notices on their behalf.³ Balanced by such factors as how much a new work damages the market for a prior work and how much of a prior work is used in a new work, the “fair use” defense allows songwriters to upload technically infringing work if the new work amounts to a critique,⁴ is in the public domain,⁵ or sufficiently transforms the original work to render it new.⁶ Content ID programs, however, don’t seem to be able to assess sufficiently the difference between content that is protected under the fair use doctrine and content that is not.

Some algorithmic enforcement programs tout near 100 percent effectiveness at spotting and blocking content.⁷ However, these programs can produce “false positives,”⁸ where legally allowable music associated with a reference file is inappropriately blocked. This is especially problematic for hip hop songwriters and others who create music by combining their own vocal or instrumental performance with work created by others⁹ and “loops” from audio libraries, such as Apple’s GarageBand.¹⁰ Although there are debates about how over-use of prior work actually dilutes the quality of today’s music, some scholars

Problem with Content ID, 13 DUKE L. & TECH. REV. 66, 69–70 (2015).

³ In *Lenz v. Universal Music Corp.*, 801 F.3d 1126 (9th Cir. 2015), Universal Music Corp. sought to block a mother’s uploaded video of her two young kids dancing to the Prince song, “Let’s Get Crazy.”

⁴ *Lennon v. Premise Media Corp.*, 556 F. Supp. 2d 310, 327 (S.D.N.Y. 2008) (holding that the filmmaker’s use of the John Lennon song “Imagine” to criticize Lennon’s pacifist stance is “transformative because [the filmmaker’s] purpose is to criticize the song’s message.”).

⁵ Not long ago, Rumblefish, an online intermediary that helps users monetize their YouTube posted content (see www.rumblefish.com), had YouTube send a take-down notice to a songwriter for posting a video that included live bird songs. Rumblefish claimed it owned the copyright to the bird songs, the kind of natural phenomenon usually in the public domain. Eventually the company backed away from its original position, most likely in response to public criticism. See *supra* note 3.

⁶ Toni Lester, *Blurred Lines—Where Copyright Ends and Cultural Appropriation Begins—The Case of Robin Thicke versus Bridgeport Music, and the Estate of Marvin Gaye*, 36 HASTINGS COMM. & ENT. LAW J. 217, 232 (2014); see also *Campbell v. Acuff-Rose Music, Inc.*, 510 U.S. 569 (1994) (holding that a parody of a previously-owned piece of music was a sufficient critique of the original to render the parody transformative).

⁷ Eugene Weinstein and Pedro Moreno, Conference Paper, Int’l Conf. on Acoustics, Speech & Signal Processing, Music Identification with Weighted Finite-State Transducers (May 2007), https://www.researchgate.net/publication/224711171_Music_Identification_with_Weighted_Finite-State_Transducers.

⁸ Ben Depoorter & Robert Kirk Walker, *Copyright False Positives*, 89 NOTRE DAME L. REV. 319, 326 (2013).

⁹ Enrico Bonadio, *The Stairway to The Day The Music Died?: Enrico Bonadio On How Litigation Is Threatening to Stifle Creativity*, THE JOURNAL (Apr. 16, 2016), <https://www.ques-tia.com/newspaper/1G1-44964477/the-stairway-to-the-day-the-music-died-enrico-bonadio>.

¹⁰ See Christiane Cargill Kinney, *Posting Cover Songs on YouTube: Music Licensing Law Explained*, DIY MUSICIAN (Mar. 28, 2012), <http://diymusician.cdbaby.com/youtube/posting-cover-songs-on-youtube-music-licensing-law-explained>.

believe this is what actually makes much of popular music innovative,¹¹ the very thing that copyright law is supposed to protect.¹²

This article will explain in greater depth how the phenomenon of false positives in online music content ID programs can hinder songwriters from creating musically innovative work. To illustrate our points, we have included a case study featuring a hypothetical songwriter, Elaine. In Part I we show how a songwriter's use of prior work can contribute to musical creativity and innovation. Part II describes YouTube's take-down notice and subsequent appeals process.¹³ Part III discusses how the fair use defense limits the extent to which Content ID programs can block innovative songwriting, particularly in the context of *Lenz v. Universal Music*,¹⁴ *Blanch v. Koons*,¹⁵ *Cariou v. Prince*,¹⁶ and *Ono Lennon v. Premise Media*.¹⁷ Part IV explains how Content ID algorithms are developed and interpreted in order to justify take-down notices and how false positives arise in connection with their interpretation and application. Part IV also discusses how the metrics used to assess Content ID effectiveness can create the false impression that the programs are effectively policing infringing content. We then explore how other metrics can be used to address this problem.

Scholars Maayan Perel and Niva Elkin-Koren observe that online platforms like YouTube resist public disclosure of their algorithms for competitive proprietary reasons, making it difficult for creative artists to craft legally protected work that would not be blocked by the algorithms.¹⁸ Perel and Elkin-Koren suggest that a regulatory framework be developed to address these "barriers of non-transparency."¹⁹ Inspired by their work, in Part V we offer methods

¹¹ Olufunmilayo B. Arewa, *From J.C. Bach to Hip Hop: Musical Borrowing, Copyright and Cultural Context*, 84 N.C. L. Rev. 547, 621–22, 639 (2006) (proposing new regulations making it easier for hip hop artists to use prior work, which the author believes will create a "potential for innovation . . . because future creators would be relatively freer to use existing material creatively and deal with issues of liability and compensation ex post.").

¹² Chris Dodd, *Copyright: Empowering Innovation and Creativity*, HUFFINGTON POST (June 10, 2013, 4:50pm), www.huffingtonpost.com/chris-dodd/copyright-empowering-inno_b_3417472.html ("But the founders of our republic considered copyright so important to unlocking the creative and economic potential of this country that they explicitly called for its protection and promotion in our Constitution.").

¹³ Christina Warren, *How YouTube Fights Copyright Infringement*, MASHABLE (Feb. 17, 2012), www.mashable.com/2012/02/17/YouTube-content-id-faq.

¹⁴ *Lenz v. Universal Music Corp.*, 801 F.3d 1126 (2015).

¹⁵ *Blanch v. Koons*, 467 F.3d 245 (2d Cir. 2006).

¹⁶ *Cariou v. Prince*, 714 F.3d 694 (2d Cir. 2013).

¹⁷ *Lennon v. Premise Media Corp.*, 556 F. Supp. 2d 310 (S.D.N.Y. 2008).

¹⁸ Maayan Perel & Niva Elkin-Koren, *Accountability in Algorithmic Copyright Enforcement*, 19 STAN. TECH. L. REV. 473 (2016).

¹⁹ *Id.* at 530–31; see also Depoorter and Walker, *supra* note 8, at 347–48, 357 (arguing that laws making it illegal to misrepresent copyright ownership should be strengthened and that defendants be allowed to sue for reverse damage awards when they win, with the costs and attorney's fees that are currently allowed).

for defining and measuring algorithmic effectiveness that both account for the risk of false positives and protect the proprietary interests of copyright holders.²⁰ We also propose a new regulatory scheme that ensures these methods are implemented properly. The proposed regulatory scheme should lead to a more equitable system for songwriters and original copyright holders and to more inventive and interesting music for fans.

I. HOW USE OF PRIOR WORK CAN PRODUCE INNOVATION IN SONGWRITING

Many songwriters compose songs today by using music production software like Apple's GarageBand to record themselves singing or playing instruments. GarageBand comes with an extensive audio library, called Apple Loops, which contains prerecorded musical, percussive and sound effect segments. Songwriters usually dedicate each live voice, instrument or loop to a different track, ultimately producing a multitrack recording in which all the tracks blend together to produce an overall work. GarageBand's licensing agreement allows customers to use these loops for multitrack commercial recordings, but restricts customers from using the loops "on a stand-alone basis . . ."²¹

Elaine, our hypothetical case study subject, is a technologically-savvy folk singer and songwriter who is worried about the threat of war. For Track 1, Elaine uses a GarageBand hip hop rhythm loop as the underlying rhythm track for a new anti-war song. Since so many songwriters use GarageBand, Elaine suspects that someone else has already used the same loop in an earlier song, possibly as an underlying rhythm track to support additional tracks of their own making. For our case, we will call the creator of the earlier song José.

Elaine is also a big fan of Jennifer's electronic sound designs, which consist of sounds found outside in everyday life that Jennifer records. One of Jennifer's most well-known pieces features a recording of New York City traffic noise. Elaine records traffic noise in San Francisco and uses that recording for Track 2 of her new song. For Track 3, Elaine sings the initial three-word phrase from the popular civil rights protest song, "We Shall Overcome"²² for five minutes. Currently, the Richmond Corporation believes it owns the rights

²⁰ As mentioned earlier, Weinstein and Moreno discuss a content ID system that promises 100 percent effectiveness. But "effectiveness" can be defined in multiple ways. We will offer different criteria and standards to measure it in Parts Four and Five. Weinstein and Moreno, *supra* note 9.

²¹ Apple Support, *Using Royalty-free Loops in GarageBand with Commercial Work*, Apple Inc. (Jan 18, 2017), <https://support.apple.com/en-us/HT201808> (quoting *The GarageBand Software License Agreement*).

²² David A. Graham, *Who Owns Will Shall Overcome?*, THE ATLANTIC (April 14, 2016), www.theatlantic.com/entertainment/archive/2016/04/we-shall-overcome-lawsuit/478068.

to “We Shall Overcome”, and is in a dispute with others who want to use the song freely because they believe it is in the public domain.²³

Finally, Amir, another hypothetical case study character, gave a TED Talk last year on the perils of war. In it, he said “War is not the answer!” Elaine pastes a three-second segment of Amir’s recorded speech onto Track 4. She calls her five minute long song, “Give It Up For Peace!”, hoping to inspire listeners not only to dance to a catchy beat, but to get more involved in peaceful anti-war protests.

By taking music and recordings of work previously created by others and mixing it together according to her own artistic instincts, Elaine is in a long line of other artists who engage in musical borrowing.

Borrowing from earlier pieces is a structural element of music creation in many genres (a tune cannot always be created from scratch by just improvising). Classical music composers such as Handel, Beethoven, Schubert, Mozart, Bach and Puccini all significantly borrowed from earlier colleagues.²⁴

As composer Jon Brantingham explains: “Steal short bits from pieces that you really like, but then change things in them. . . . In the grand scheme, if you become a great, and scholars are dissecting your music in the future, they will look at it and say: ‘Ah, clearly here, he was influenced by Jon Brantingham’s Piano Sonata No. 1 . . .’”²⁵

While it might seem counterintuitive to think that musical borrowing contributes to the creation of innovative music, Elaine’s use of prior work is “not necessarily antithetical to originality or creativity”²⁶ because it could be argued that she has rearranged and transformed it to such an extent that it conveys to the public “new information, new aesthetics, new insights and understandings.”²⁷ This has come to be known as the “transformative use” standard in

²³ Elizabeth Blair, *Who Owns ‘We Shall Overcome’? All of Us, A Lawsuit Claims*, NAT’L PUB. RADIO: ALL THINGS CONSIDERED (April 13, 2016), <http://www.npr.org/2016/04/13/474120870/we-shall-overcome-foundation-wages-copyright-war-over-civil-rights-anthem>.

²⁴ Bonadio, *supra* note 11. See also Hanna Brooks Olsen, *Beg, Borrow, Steal: Why It’s OK That Nothing You Make Is Original*, CREATIVE LIVE (June 27, 2014), <http://blog.creativelive.com/why-stealing-is-creative>.

²⁵ John Brantingame, *Why It Is Okay to Copy Other Composers (Preferably Public Domain)*, ART OF COMPOSING, <https://www.artofcomposing.com/good-composers-borrow-great-composers-steal>.

²⁶ Arewa, *supra* note 13, at 631 (“The conceptions of creativity and originality that pervade copyright discussions are incomplete or inaccurate models of actual musical production, particularly the collaborative aspects of musical practice evident in borrowing.”).

²⁷ See *Blanch*, 467 F.3d at 253 (citing *Castle Rock Ent., Inc. v. Carol Pub. Grp., Inc.*, 150 F.3d 132, 142 (2d Cir. 1998)). See generally Lester, *supra* note 8 (stating there are dangers of unethical musical borrowing and appropriation of black American music in particular, and by implication, the music of other minorities and indigenous groups, historically exploited to the detriment of black artists without sufficient attribution or compensation). When done appropriately, ethically, and with this legacy in mind, it is possible that use of prior work can be innovative and worthy of legal protection.

U.S. copyright law, per the seminal case *Campbell v. Acuff-Rose*. The Court of Appeals for the Second Circuit invoked this doctrine in *Blanch v. Koons*,²⁸ holding that artist Jeff Koons' collage, which included part of a photograph of a model's legs taken by fashion photographer Andrea Blanch, transformed Blanch's work such that Koons' unauthorized use did not constitute copyright infringement.²⁹ Seven years later, the same court held that visual artist Richard Prince's unauthorized use of "key portions of . . . [photographer Patrick Cariou's] pictures of Ratafarians," was protected under the fair use doctrine because it "transformed the photographs into something new and different."³⁰

There is a thin line, however, between being inspired by or paying homage to prior work and inappropriately plagiarizing or stealing it under copyright law. This, at least, is the opinion of José, Jennifer, the Richmond Organization, and Amir after YouTube's Content ID algorithm blocks the new song that Elaine has uploaded. When Elaine files a counter-notification challenging the YouTube action,³¹ each of the four deny her request to upload the piece.

The next section provides a more in-depth explanation of how the take-down notice process works and the extent to which algorithms drive take-down notice creation.

II. YOUTUBE'S TAKE DOWN NOTICE AND APPEALS PROCESS

Section 512 of the Digital Millennium Copyright Act of 1998 (DMCA) grants companies like YouTube a safe harbor against copyright theft claims if those companies provide 1) content owners with a mechanism for lodging complaints, and 2) alleged infringers with a process for challenging those complaints.³² Large companies are the main beneficiaries of YouTube's Content ID program because they "own exclusive rights to a substantial body of original material that is frequently uploaded by the YouTube user community."³³

Copyright owners can respond in several ways if they feel a song uploaded to YouTube violates their exclusive rights under the Copyright Act. They can "mute audio that matches their music, block a whole video from being viewed, monetize the video by running ads against it, [or] track the video's viewership statistics."³⁴ When Elaine's new uploaded song is blocked, YouTube gives her a "strike." If Elaine gets three strikes, YouTube can terminate

²⁸ *Id.* at 247.

²⁹ *Id.* at 253 (citing *Castle Rock Ent.*, 150 F.3d at 142).

³⁰ *Cariou*, 714 F.3d at 711.

³¹ YouTube Help, *How Content ID Works*, YOUTUBE, <https://support.google.com/youtube/answer/2797370?hl=en>. See also YouTube Help, *Copyright Strike Basics*, YOUTUBE, <https://support.google.com/youtube/answer/2814000?hl=en>.

³² 17 U.S.C. § 512(c)(1)(A)(iii) and (C) (2016).

³³ *How Content ID Works*, *supra* note 33.

³⁴ *Id.*

her account.³⁵ Elaine has the option of contacting the claimant directly and asking for a retraction or submitting a counter-notification stating that the content was removed incorrectly.³⁶ In our case study, she filed a counter-notification, but was rejected.

If José, Jennifer, Amir and the Richmond Organization deny Elaine's request without doing a fair use analysis first, however, they do so at their own peril. In the 2015 case *Lenz v. Universal Music*,³⁷ Universal Music Corp. was sued after it requested that YouTube block a mother's video of her two young children dancing to a song owned by Universal and originally recorded by the popular performer Prince.³⁸ The mother claimed that Universal only assessed how much of the Prince song was used and did not consider factors associated with the fair use doctrine, such as free speech issues. In granting its decision, the Court of Appeals was concerned that copyright owners were overzealously exercising their rights under the DMCA. It concluded that "the statute requires copyright holders to consider fair use before sending a takedown notification, and that there is a triable issue as to whether the copyright holder formed a subjective good faith belief that the use was not authorized by law."³⁹

YouTube warns copyright owners that they should not abuse the process by submitting frivolous claims,⁴⁰ including claims relating to "content released under Creative Commons or similar free/open licenses, Public Domain footage, recordings, or composition, clips from other sources used under fair use principles."⁴¹ Partly in response to *Lenz*, YouTube now even offers to fund selectively blocked users who wish to challenge inappropriate take down notices in court.⁴² Since this selection is limited to a small number of well-known users, most songwriters entitled to rely on the fair use defense continue to have their music blocked.⁴³

³⁵ YouTube Help, *Copyright Strike Basics*, YOUTUBE, <https://support.google.com/youtube/answer/2814000?hl=en>.

³⁶ *d.*

³⁷ *Lenz*, 801 F.3d 1126 (2015).

³⁸ *Id.* at 1148.

³⁹ *Id.* at 1148, 1154.

⁴⁰ YouTube Help, *What Kind of Content Is Eligible for Content ID?*, YOUTUBE, <https://support.google.com/youtube/answer/2605065?hl=en>.

⁴¹ YOUTUBE, *supra* note 42. The company also cautions owners that they might be subject to legal action if they misuse the take down notice process; see also YouTube Help, *Submit A Copyright Takedown Notice*, YOUTUBE, <https://support.google.com/youtube/answer/2807622?hl=en>.

⁴² YouTube, *YouTube Fair Use Protection*, YOUTUBE, <https://www.YouTube.com/yt/copyright/fair-use.html#yt-copyright-protection>. See also Sarah Perez, *YouTube Says It Will Offer Legal Protection of Up To \$1 Million for Select Video Creators Facing DMCA Takedowns*, TECHCRUNCH (Nov. 19. 2015), <http://techcrunch.com/2015/11/19/YouTube-says-it-will-offer-legal-protection-to-some-video-creators-facing-dmca-takedowns>.

⁴³ Perez, *supra* note 44.

In our hypothetical case, Elaine is facing several claims against “Give It Up For Peace!” José contends Elaine’s use of the hip-hop loop captures an inappropriate percent of a key component of his song. Jennifer claims Elaine used her traffic noise recording without permission. Amir argues he owns the copyright to the three-second phrase in his TED Talk, and that Elaine’s song will mistakenly cause the public to believe that he endorses the anti-war protests that will no doubt be inspired by Elaine’s song. Finally, the Richmond Organization claims it owns the copyright to “We Shall Overcome.” If Elaine were to challenge the above rationales in court, she might very well win her claims in light of relevant statutory and case law on the grounds that her song is creative, innovative and transformative, and that some of the prior work she used, like excerpts from the song “We Shall Overcome,” are in the public domain.

III. WHAT COPYRIGHT LAW SAYS ABOUT USE OF PRIOR WORK AND INNOVATION IN MUSIC

The U.S. Constitution provides that: “Congress shall have Power . . . To promote the Progress of Science and useful Arts, by securing for limited Times to Authors and Inventors the exclusive Right to their respective Writings and Discoveries.”⁴⁴ While the Constitution does not directly refer to innovation, the seeds for this concept are found in how the courts interpret the statutory requirement that copyrighted works must be “original.”⁴⁵ Courts interpreting the law have traditionally left us with the “pervasive assumption . . . that copyright gives incentives to innovate that result in greater production of artistic works.”⁴⁶

Additionally, the existing exceptions to the limited monopoly granted under the Copyright Act suggest that Congress saw the value in innovation. As stated in the introduction to this article, the Copyright Act allows songwriters to use prior work if the use relates to a critique, is not too substantial, and has not significantly hurt the original owners’ prospects for making money.⁴⁷ Further, songwriters can use anything that is already in the public domain, including works whose original copyrights have expired, or works deemed not sufficiently creative or original to warrant copyright protection.⁴⁸

⁴⁴ U.S. CONST. art. I, § 8, cl. 8.

⁴⁵ 17 U.S.C. § 102(a) (2015) (providing that “copyright protection subsists . . . in original works of authorship fixed in any tangible medium of expression.”).

⁴⁶ Olufunmilayo B. Arewa, *Creativity and the Law: Creativity, Improvisation, and Risk: Copyright and Musical Innovation*, 86 Notre Dame L. Rev. 1831 (2011). See *supra* note 9 citing Stewart E. Sterk, Rhetoric and Reality in Copyright Law, 94 Mich. L. Rev. 1197, 1202–03 (1996) (noting the prominence of incentive language in Supreme Court copyright cases).

⁴⁷ 17 U.S.C. § 107 (2015).

⁴⁸ Rich Stim, *The Public Domain—Copyright Overview*, STANFORD UNIVERSITY LIBRARIES, <http://fairuse.stanford.edu/overview/public-domain/welcome>.

Copyright law protects the expression of ideas, but not the ideas themselves. A work is not considered an expression if it constitutes “*scenes a faire*”—frames for stories “used so many times that they are considered to be generic and not unique or original.”⁴⁹ Thus, an outline for a play about a devious and power hungry billionaire would probably not be copyrightable, but a script making the billionaire an ex-con and former drug user that describes the specifics of his prison experience, including who his enemies were and what they did to him in prison, might be considered protectable expression under the Copyright Act.

Turning to our hypothetical case, Elaine explains that she owns GarageBand software and thus has a license to use the hip hop loop mentioned above. Further, even if she did not have a license, she could contend that the loop is not original enough to justify its being granted copyright protection. This is because courts usually treat standard, commonly used rhythms as if they too were *scenes a faire*.⁵⁰ Unfortunately, YouTube’s algorithm blocks substantially similar audio matches, regardless of Elaine’s fair use of the hip hop loop. As one songwriter experiencing a similar problem complained:

Musicians are using these ROYALTY FREE jingles and loops to mix and sell their own music. YouTube pings the soundtracks and the musician who used APPLE GarageBand . . . in their songs claims the LOOP as their original music. I PAID FOR THE DARN TRACKS and many were posted well before the musician went and made their version. I AM NOT using the mixed musician’s version. I am only using and remixing APPLE TRACKS that are 100% ROYALTY FREE!!!!!!”⁵¹

Similarly, with respect to Jennifer’s traffic noise recordings, Elaine can argue that she did not use Jennifer’s recordings; she made her own recordings of traffic noise. Elaine can also probably successfully defend her use of lyrics to “We Shall Overcome” because of the song’s questionable copyright history.

Lastly, Elaine’s use of the Amir recording would most likely be deemed protected political speech, just as was the case in *Ono-Lennon v. Premise Media*.⁵² In this case, the district court concluded that a film company’s use of a fifteen second clip of the John Lennon song “Imagine” in order to critique the song’s anti-war message was allowable free speech under the Copyright Act. It said:

⁴⁹ Lester, *supra* note 8, at 226. See also *Allen v. Destiny’s Child*, 2009 U.S. Dist. LEXIS 6300, 29, 32 (2009) (“Copyright protection does not extend to ideas, plots, dramatic situations and events.” . . . These kinds of things are considered generic “*scenes a faire*.”).

⁵⁰ *Id.* at 239–41.

⁵¹ SOLARPOWER, *GarageBand Loops Soundtrack Pro Are Being Claimed As Copyright*, YOUTUBE HELP FORUM (Oct. 1, 2011), <https://productforums.google.com/forum/#!topic/YouTube/FY0-XOo7boE>.

⁵² *Lennon*, 556 F. Supp. 2d 310 (2008).

Defendants' use . . . is *transformative* because their purpose is to criticize the song's message. . . . the amount and substantiality of the portion used is reasonable in light of defendants' purpose. Although "Imagine," as a creative work, is at the core of copyright protection, and defendants' use of the song is at least partially commercial in nature, the weight of these factors against a finding of fair use is limited given that defendants' use is *transformative*.⁵³

In contrast to the *Ono-Lennon* case, Elaine is using Amir's speech to concur with her own views. However, her use is in line with the *spirit* of the *Ono-Lennon* decision because it constitutes political speech. As such, it would probably be deemed protected speech as well.

As the above discussion indicates, Elaine has a strong chance of winning her claims against José, Jennifer, the Richmond Organization and Amir. However, to win she will have to engage in costly and time-consuming litigation. That is why it would be better to look at how the interpretation of the output from the algorithms that drive the original take-down notices can be improved to avoid these conflicts to begin with. Part IV below will discuss the general limitations that arise with respect to how Content ID algorithms are developed and applied. We will continue to refer to our hypothetical case protagonist Elaine wherever appropriate in order to illustrate our points.

IV. THE ALGORITHMS BEHIND CONTENT ID AND THE ASSESSMENT OF THEIR EFFECTIVENESS

A. *Characteristics, Benefits, and Limitations of Content Recognition Algorithms*

Content recognition algorithms work by comparing a new content piece (e.g., an audio or a video clip Elaine uploaded to YouTube) to pieces already in a database (e.g., to all the content already uploaded to YouTube). There are numerous ways in which data associated with a piece of uploaded music like Elaine's could be analyzed, including how Elaine pronounces the words to "We Shall Overcome" in her song,⁵⁴ the order in which the hip hop beats appear in the song, the exact onset and end point in the song,⁵⁵ where the traffic noise sounds are situated, the frequency of the sound waves generated by clips from the recording of Amir's speech,⁵⁶ and so on.

Analyzing all of the data in Elaine's song as a single piece of content is not convenient. Instead, Content ID algorithms transcribe the data into

⁵³ *Id.* at 327.

⁵⁴ Adam L. Buschsbaum & Raffaele Giancarlo, *Algorithmic Aspects in Speech Recognition: An Introduction*, 2 J. of Experimental Algorithmics 1 (1997).

⁵⁵ Simon Dixon, *Onset Detection Revisited*, PROC. OF THE 9TH INT'L CONF ON DIGITAL AUDIO EFFECTS (DAFx'06) (Sept. 19, 2006), http://www.dafx.ca/proceedings/papers/p_133.pdf.

⁵⁶ User Manual, Soundtrack Pro 3, *What Is Sound?*, <http://documentation.apple.com/en/soundtrackpro/usermanual/index.html#chapter=B%26section=1%26tasks=true>.

smaller units of content that are then compared to transcribed units of content from other pieces of music in the database. For the purpose of giving the reader a sense of how Content ID algorithms work in general, we discuss two of the most commonly used ones—“hashing” and “search” algorithms.⁵⁷ We then discuss additional challenges with using Content ID algorithms, including the quality of data used as input to the algorithms, fair use issues, and metrics used to assess the performance of the algorithms.

B. *Hashing Algorithms*

Hashing is the transformation of a string of values into a (typically) shorter “hash value” (a “key”). In the case of audio content such as Elaine’s uploaded song, hashing would typically associate every basic time-unit in the content piece with a short sequence of bits.⁵⁸ Bits are basic units of information with only two values—e.g., 0 and 1.

Hashing simplifies the resource-intensive process of comparing a long string of values in one song to a long string of values in another song.⁵⁹ If the long string of values is converted to a unique shorter string of bit values, the content comparison can be done faster. Generating unique “keys” for different strings of original values is a goal of all hashing algorithms; however, uniqueness is not always achieved. It is possible that two very different pieces of audio content will generate the same or similar hash values.

Cases in which two otherwise different pieces of content are transformed into the same or very similar hash values are referred to as “collisions” or “clashes.” They represent failure at the very task a Content ID algorithm is designed to perform.⁶⁰ Yet, all hashing Content ID algorithms have a theoretical probability of generating collisions because of the fact that they reduce the original content pieces to smaller sets of values.

“Robust” hashing aims to make clashes less likely. Hash values are generated using an audio clip’s “robust features,” which are statistics associated with audio signals that remain relatively immune to processing. For example, this might ensure that the file format in which a song is stored (possibly

⁵⁷ Weinstein and Moreno, *Music Identification*, *supra* note 9.

⁵⁸ Jaap Haitsma, Ton Kalker and Job Oostveen, *Robust Audio Hashing for Content Identification*, CONTENT-BASED MULTIMEDIA INDEXING (2001), <http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.16.2893>.

⁵⁹ Detecting onset phenomenon is particularly challenging, especially in polyphonic music. *Supra* note 58, at 133. (“At first sight, onset detection is a well-defined task: the aim is to find the starting time of each musical note (where a musical note is not restricted to those having a clear pitch or harmonic partials). However, in polyphonic music, where nominal simultaneous notes (chords) might be spread over tens of milliseconds, the definition of onsets starts to become blurred. Likewise, instruments with long attack times (e.g. flute) produce notes for which it is difficult to define an unambiguous and precise onset time.”).

⁶⁰ Jeff Preshing, *Hash Collision Probabilities*, PRESHING ON PROGRAMMING (May 4, 2011), <http://preshing.com/20110504/hash-collision-probabilities>.

with different compression and noise) does not affect the correct identification of two otherwise identical pieces of music.⁶¹ Scholars Jaap Haitsma, Jon Kalker and Job Oostveen describe a robust audio hashing algorithm in which a 32-bit hash value for every frame of an audio clip is extracted by selecting 33 non-overlapping frequency bands and mapping the signs of energy differences (simultaneously along the time and frequency axes) to the bits of the hash string.⁶² Approximately 3 seconds of audio contain about 256 frames, referred to as a “hash block.” The difference between two 3-second audio clips is assessed based on a metric of “distance” between the two derived hash blocks.⁶³ The distance could be calculated, for example, as the number of positions at which the two hash sequences are different.

The robust hashing algorithm decides whether to declare two audio clips the same based on whether the distance between their hash values is below a prespecified threshold. The specification of the threshold affects the accuracy with which the Content ID algorithm identifies a piece as infringing or non-infringing. The smaller the threshold value, the smaller the probability of the algorithm reporting a false positive because the two hash sequences would have to be nearly identical for the algorithm to declare a match. A low threshold value would not necessarily help reduce the number of false positives, however, if the transformation of the original content into non-unique hash values creates the similarities between the two hash sequences.

C. Search Algorithms

Instead of transforming an original music piece as is done by hashing algorithms, search algorithms deconstruct the piece into a sequence of audio events, simultaneously creating an inventory of “music phonemes”— or elementary units of music— as well as the sequence of phonemes best representing each song in the database. In this process, the size or number (referred to as a “dimension”) of the characteristics of a piece of music is reduced to a smaller set of representative characteristics (an “alphabet”) that, when assembled in the right combinations, can generate (“transcribe”) any song in the database.⁶⁴ Search algorithms “learn” continuously: as songs are added, they constantly revise their set of phonemes to represent the songs in the database better. They then retranscribe the songs in the database with the new “alphabet.”⁶⁵

With a search Content ID algorithm, the system identifies a match for a fragment of a piece of music in a stream of audio by continuously calculating the probability that the events stored in the database, as represented by the elementary units of music, are the generators of the new audio clip. If the

⁶¹ Haitsma, Kalker, et al., *supra* note 61.

⁶² *Id.*

⁶³ *Id.*, at 3, 4.

⁶⁴ Weinstein & Moreno, *supra* note 9, at 1.

⁶⁵ Weinstein & Moreno, *supra* note 9.

calculated probability is higher than a prespecified threshold, the new audio clip is considered infringing. As in the case of hashing, the percentage of false positives can be controlled by the set threshold value. A higher value for the threshold would generally result in fewer false positives.

Elaine's song may be flagged by a search algorithm given Elaine's use of elementary units already in YouTube's database. When the algorithm decomposes her song into the set of elementary music units, the song may be represented by the same music phonemes in the same combination as content pieces already in the database. Thus, the sound waves of Jennifer's recording of traffic noise, for example, might be assessed as having peaks, lows, and frequencies that are similar to Elaine's song.

D. *Data Quality*

The correct classification of two audio pieces as similar is challenging not only due to issues with Content ID algorithm design but also due to issues with data quality. Scholars Golik, Harb, Misra, Riley, Rudnick and Weinstein give an example of how the performance of an otherwise highly accurate search algorithm deteriorates when the algorithm is used on music recordings from mobile phones.⁶⁶ The quality of the data from such recordings is low because the recordings are "marked with substantial quality degradation of the test audio, a significant spectral tilt introduced by the mobile phone microphone, as well as noise and channel characteristics introduced by recording in a real-world environment."⁶⁷ When data quality is low, the inputs to Content ID algorithms may be a poor representation of the characteristics of content pieces. The output of Content ID algorithms based on such unreliable input data is, naturally, imperfect.

E. *Fair Use Recognition*

Even if content recognition algorithms are able to identify correctly that two uploaded songs are similar, they are not able to assess whether the allegedly infringing song is in the public domain, is a parody, or is sufficiently transformative to constitute the fair use of a previously copyrighted work. Algorithms can recognize whether elements of Elaine's songs match elements of existing works, but they cannot assess the purpose for which Elaine used those songs.

In addition to problems with algorithmic design, problems with data quality, and the lack of a method for assessing fair use under copyright law, the way in which online providers use and report metrics to assess algorithmic effectiveness is also of some concern.

⁶⁶ Pavel Golik, et al., *Mobile Music Modeling, Analysis and Recognition*, RESEARCH AT GOOGLE, <https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/37754.pdf>.

⁶⁷ *Id.* at 1.

F. *Metrics for Content ID Algorithm Effectiveness*

When an algorithm recommends classifying content as “infringing” or “not infringing,” there are four possible outcomes: true positives, true negatives, false positives, and false negatives.

- If the algorithm returns a “positive” recommendation, thereby identifying the piece of music as infringing, and the identification is correct, it is considered a “true positive.” For example, if Elaine’s song is considered infringing and the algorithm correctly identifies it as such, the identification would be a “true positive.”
- If the algorithm returns a “positive” recommendation, but the identification is incorrect, it is considered a “false positive.” For example, if Elaine’s song is considered non-infringing, but the algorithm declares it infringing, the song identification would be a “false positive.”
- If the algorithm returns a “negative” recommendation, thereby identifying a piece of music as non-infringing, and the identification is correct, it would be considered a “true negative.” For example, if Elaine’s song is considered non-infringing and the algorithm declares it non-infringing, the identification would be a “true negative.”
- If the algorithm returns a “negative” recommendation, but the identification is incorrect, it would be considered a “false negative.” For example, if Elaine’s song is considered infringing, but the algorithm declares it non-infringing, the identification would be a “false negative.”

The overall accuracy for a classification algorithm is calculated as the sum of the true positives and the true negatives divided by the total number of content pieces evaluated.⁶⁸ When a classification algorithm is reported as being 99 percent accurate, this means that the algorithm correctly identifies 99 percent of all content pieces. The remaining 1 percent are incorrectly classified by the algorithm. The problem with reporting the total accuracy of an algorithm is that the metric does not differentiate how well the algorithm did with regard to the false positives and the false negatives in these remaining 1 percent of cases. Are the majority of those 1 percent of wrongly classified cases false negatives, hurting mostly major content owners? Or are they false positives, hurting mostly independent artists such as Elaine?

There are alternative metrics that allow for differentiating an algorithm’s ability to identify false positives and false negatives. The following are four examples of alternative metrics:

- *The True Positive Rate (TPR)*, also referred to as “sensitivity,” is the ratio of true positives to true positives plus false negatives. It reflects the likelihood that the algorithmic copyright enforcement system finds infringing

⁶⁸ These are standard metrics for evaluating algorithm accuracy. See, e.g., GALIT SHMUELI ET AL., *DATA MINING FOR BUSINESS ANALYTICS: CONCEPTS, TECHNIQUES, AND APPLICATIONS WITH XLMINER* ch. 5 (3rd ed. 2016).

content pieces. The sensitivity is the percentage of all infringing cases that are correctly identified as infringing by the algorithm.

- *The True Negative Rate (TNR)*, also referred to as “specificity,” is the ratio of true negatives to true negatives plus false positives. It reflects the likelihood that the algorithmic copyright enforcement system correctly excludes non-infringing content pieces. The specificity is the percentage of all non-infringing cases that are correctly identified as non-infringing by the algorithm.
- *The Positive Predictive Value (PPV)*, also referred to as “precision,” is the ratio of true positives to true positives plus false positives. It reflects the likelihood that a content piece classified as infringing is actually infringing. The precision is the percentage of all content pieces marked by the algorithm as infringing that are indeed infringing.
- *The Negative Predictive Value (NPV)* is the ratio of true negatives to true negatives plus false negatives. It reflects the likelihood that a content piece classified as non-infringing is actually non-infringing. The NPV is the percentage of all pieces marked by the algorithm as non-infringing that are indeed non-infringing.

The TPR and the TNR reflect how effective the algorithm is at finding infringing or non-infringing pieces among all content pieces on the platform. The PPV and the NPV indicate how much the recommendation of the algorithm should be trusted when it comes to classifying a piece of content as infringing (in the case of the PPV) and non-infringing (in the case of the NPV). The PPV should be of particular interest when considering policies aiming to foster innovation and protect independent artists. A high value for the PPV for an algorithm would indicate that the algorithm does not lead to unjustified blocking or monetizing of content.

Note that although the terms “accuracy” and “precision” are often used interchangeably in practice, they have very specific meaning in the context of evaluating algorithmic performance. Thus, interpretation of the reports by online providers should be done carefully. For example, YouTube has reported that its Content ID is “99.7% precise for recordings on file.”⁶⁹ If “precision” is used in the same sense as the PPV, this would indicate that 99.7 percent of all content pieces identified as infringing by the Content ID algorithm are indeed infringing. If “precision” is used in the sense of “accuracy,” however, the interpretation would be that 99.7 percent of all content pieces are correctly classified as either infringing or non-infringing. This would not provide information about how the algorithm treats false positives and false negatives separately.

⁶⁹ Hannah Karp, *Industry Out of Harmony with YouTube on Tracking of Copyrighted Music*, WALL ST. J. (June 28, 2016), <http://www.wsj.com/articles/industry-out-of-harmony-with-YouTube-on-tracking-of-copyrighted-music-1467106213>.

A system for better metrics may still fail because of poor data quality and factors outside the company's control. For example, according to YouTube, fewer than 1 percent of the claims submitted through Content ID by the music industry are disputed by the uploaders.⁷⁰ On the one hand, this might suggest that the Content ID algorithm has a 99 percent PPV (i.e., that it identifies 99 percent of all infringing cases correctly), leading YouTube to feel good about how its Content ID system is working. On the other hand, the favorable algorithm performance metric value may simply be caused by the fact that small indie songwriters like Elaine forgo challenging take-down notices because they cannot afford the high costs of litigation.⁷¹ As discussed in Part II above, YouTube has created a new program wherein it offers to fund the costs of defending unfair infringement claims brought against users by clients, but the program appears to be small in scope: Specifically, YouTube says that it will selectively offer legal support to a handful of videos that represent "clear fair uses which have been subject to DMCA takedowns. . . . only a small number of videos will be offered legal support."⁷²

In light of the analysis in this section, we conclude that there are four main problems that arise in connection with how Content ID algorithms are used by online providers. They are:

1. Content identification errors associated with the design of algorithms themselves;
2. Content identification errors resulting from poor data quality;
3. Content identification errors resulting from the inability to assess fair use even when music content similarity is correctly identified; and
4. Inadequate use and reporting of appropriate metrics for Content ID algorithm performance.

Our recommendations in Part V offer possible ways to address some of these concerns, focusing on the third and the fourth issues in particular.

V. RECOMMENDATIONS

Effective copyright enforcement is undoubtedly difficult. Challenges arise from the difficulty of separating copyright-eligible expression from unprotected ideas, the need to process vast amount of content, the imbalance of power that exists in how disputes are handled,⁷³ and the legitimate desire of Content ID platforms to keep their information confidential. It is important to reemphasize, however, that innovative fair use in music can be hindered when the music of a creative artist like our case study subject Elaine is incorrectly blocked by a Content ID program.

⁷⁰ *Id.*

⁷¹ Depoorter & Walker, *supra* note 10, at 319, 326.

⁷² Perez, *supra* note 44.

⁷³ *Id.*

In this article, we have focused specifically on the challenges of effective copyright enforcement when Content ID systems use algorithms to detect infringing content pieces. Thus, our recommendations center around the structure and use of Content ID systems with algorithmic enforcement, with the goal of reducing the number of false positives and mitigating costs to songwriters and other creative artists that occur as a result.

A. *Recommendation #1: Increase Human Involvement in the “Training” of Algorithms*

As we explained in Part IV, the units into which music is transcribed or the robust features in hashing are extracted by algorithms. Algorithms are then “trained” on the existing content pieces to detect similar units in new content pieces. If the content pieces used as training data are improperly labeled as “infringing” or “non-infringing,” the algorithm will not “learn” the correct classification, and will perform poorly on new content pieces.

Content ID algorithms can detect similarity between content pieces based on the pieces’ audio characteristics; however, as explained in Part I, detecting similarity in content pieces is not sufficient to determine whether a piece is infringing. Human intervention in determining whether a content piece is not only similar, but also *infringing*, and then labeling the piece properly in the database, can be critical for the proper training of Content ID algorithms. Humans are able to consider fair use and *scenes a faire* factors that are not easy to determine based merely on the audio characteristics of content pieces.

There is, of course, always a possibility of human error—and this is a key reason why copyright enforcement is generally a challenging process. For example, one of the issues raised in the *Lenz* case discussed in Part II was that the employee assigned to assess the extent to which uploaded music was illegally copied from Universal’s roster of songs did not evaluate whether or not the uploaded music was a legally allowable fair use of that music.⁷⁴ This was one of the chief reasons Universal lost the lawsuit.⁷⁵

Further, as artificial intelligence expert Danielle Keats Citron points out, policy distortions may arise when “possibly biased code writers, who lack policy knowledge, translate policy from human language to code.”⁷⁶ In general, it is difficult to eliminate the disparity between the algorithmic interpretation of the law and the law as it operates in practice.⁷⁷

⁷⁴ *Lenz*, 801 F.3d at 1149.

⁷⁵ *Id.*, at 1166 (“Copyright holders cannot shirk their duty to consider—in good faith and prior to sending a takedown notification—whether allegedly infringing material constitutes fair use, a use which the DMCA plainly contemplates as authorized by the law.”).

⁷⁶ Maayan Perel and Nica Elkin-Koren, *Accountability in Algorithmic Copyright Enforcement*, *supra* note 20, at 80–81. See also, Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1252–53 (2008).

⁷⁷ Harry Surden, et al., *Representational Complexity in Law*, 11 INT’L CONF. ON ARTIFICIAL INTELLIGENCE & LAW 193, 193 (2007).

These challenges can be mitigated by requiring that the training data for Content ID algorithms, which allows content providers to discriminate between infringing and non-infringing pieces, is evaluated periodically not only by coders, but also by people with legal expertise. *Educated and informed* human intervention, combined with the rest of our recommendations below, are critical components of the alternative scheme we propose here.

B. *Recommendation #2: Validate Algorithmic Output by Training Algorithms Themselves to Assess the Differences Between Infringing and Noninfringing Pieces of Music*

False positives are a natural consequence of the use of non-human methods for detection.⁷⁸ A complementary recommendation to our first recommendation is to improve continuously the algorithms' own ability to differentiate between infringing and non-infringing content. It is possible to train algorithms to be more effective by keeping track of the biases that algorithms introduce by studying the characteristics of content pieces that were correctly classified as infringing and then comparing them to the characteristics of content pieces that were false positives.

To accomplish this goal, one needs access to the right data. Online intermediaries should be required to store information about all matched pieces of content, as well as the resolution of disputes between content providers and individual users. The process for submitting claims should be streamlined—for example, an individual user submitting a claim can select from a prespecified list of reasons for the claim. Algorithms should be made aware of common public domain materials. This information can then be used for training algorithms to recognize not only the similarity in audio patterns but also more nuanced differences in the music pieces, thus attempting to capture information about whether the use of the piece can be classified as fair use.

C. *Recommendation #3: Assess Algorithmic Performance with Relevant Metrics*

As explained in this article, the different metrics of algorithm performance accuracy emphasize different behaviors. Systems designed to demand accountability and foster innovation should focus on metrics that promote the use of algorithmic copyright enforcement that emphasizes the correct identification of the infringing content pieces and minimizes the occurrence of false positives. Thus, instead of measuring algorithm effectiveness by overall accuracy, accountability should include the reporting of other measures, such as the TPR, the TNR, the PPV, and the NPV—all of which were described in Part IV of this article. In particular, the PPV would allow the assessment of how

⁷⁸ 17 U.S.C. § 107 (2016).

a Content ID algorithm treats small content providers like Elaine from our case study.

D. *Recommendation #4: Require Algorithmic Performance Metrics to Be Tracked and Reported in Greater Depth*

We propose that online platform providers be required to track and publicly report the results of algorithm performance metrics that explicitly penalize algorithms with a high incidence of false positives. We understand that any proposed new regulations requiring online platforms to report information about their algorithms will be met with resistance because of fears about reverse engineering and trade secret theft; however, we believe that our proposal will not contribute to this problem for the reasons outlined below.

Competitors and other interested parties are sometimes able to figure out how content providers' algorithm programs work when there is limited information available publicly. For example, Google publishes a Transparency Report⁷⁹ that includes copyright takedown notices, domains being specified in those takedowns, and top copyright owners.⁸⁰ When Glen Gabe, a digital marketing expert, analyzed the Google Transparency Report data, he was able to extract useful information about the percentage of one's indexed URLs that need to be subject to takedown requests before Google's Pirate algorithm gets activated.⁸¹ Our proposal, however, does not ask content providers to make their data or process public. Instead, we only suggest that appropriate metrics of algorithm performance be reported publicly.

Further, Section 1201 of the DMCA's anti-circumvention, anti-reverse engineering provisions attempts to prevent outsiders from inappropriately reverse engineering Content ID algorithms.⁸² Although it has not always done

⁷⁹ See GOOGLE TRANSPARENCY REPORT, <http://www.google.com/transparencyreport>.

⁸⁰ Perel and Elkin-Koren, *supra* note 20.

⁸¹ Glenn Gabe, *Google's Pirate Algorithm and DMCA Takedowns | Exploring the Impact Threshold*, G-SQUARED INTERACTIVE (Dec. 9, 2013), <http://www.gsqi.com/marketing-blog/google-pirate-algorithm-dmca>.

⁸² 17 U.S.C. § 1201. See also Myron Hecht, *Reconciling Software Technology and Anti-Circumvention Provisions in the Digital Millennium Copyright Act*, 2004 UCLA J.L. & TECH. 3 (2004) (stating that "courts have found that software containing any protection measure would fall under the DMCA's anti-circumvention provisions. Moreover, software copyright owners can easily modify existing programs to incorporate copy or access control measures. They can then use the DMCA to enjoin the sale or distribution of any software that emulates their product or can read the files produced by their product by characterizing such emulation programs as circumvention. The net result is to inhibit competition from "clone" programs and after-market compatible products (such as printer toner cartridges) to preserve monopolies").

so effectively,⁸³ at a minimum, the provision serves as an impediment to reverse engineering.⁸⁴

Our proposal is similar to a proposal put forth by the U.S. Food and Drug Administration's (FDA) task force on trade secrets and asserted proprietary ingredients in food products and cosmetics. The task force states that "trade secrets have limited value for public disclosure, and that the value for public disclosure of other types of data, such as clinical trial results and adverse event reports, is significantly greater."⁸⁵ As is the case with the FDA task force suggestion only to focus on clinical trial results and event reports, we recommend that the focus remain on measuring the accuracy and effectiveness of the Content ID algorithms, rather than the models themselves or the data that are used to create those models.⁸⁶ The U.S. Copyright Office already has the authority to grant exemptions to the circumvention provisions of the DMCA, and it solicits input from relevant stakeholders every three years to determine if this should occur.⁸⁷ If any doubt arises that the aforementioned proposal is in contravention of those provisions, we recommend that the U.S. Copyright Office render a determination that it is not.

⁸³ The Electronic Frontier Foundation recounts one particular story of a team of researchers at Princeton University, Rice University and Xerox who tried to figure out how protective watermarking of digital music worked pursuant to a contest sponsored by the Recording Industry Association of America (RIAA). The team was threatened with a lawsuit by the RIAA when they attempted to discuss the results of their research at an academic conference. After the researchers commenced a lawsuit to protect their interests, the initial threat was rescinded. *Unintended Consequences—Sixteen Years Under the Digital Millennium Copyright Act*, ELECTR. FRONTIER FOUND., 5–6 (Sept. 2014), <https://www.eff.org/files/2014/09/16/unintendedconsequences2014.pdf>, citing Pamela Samuelson, *Anticircumvention Rules: Threat to Science*, 293 SCIENCE 2028 (Sept. 14, 2001).

⁸⁴ Ultimately, the DMCA was not able to stop the team of researchers at Princeton University, Rice University and Xerox from publishing their work reverse-engineering the protective watermarking of digital music. The researchers were backed by the Electronic Frontier Foundation, their academic institutions, and volunteer legal counsel. *Supra* note 85. However, section 1201 can be a deterrent to those who do not have access to the same resources to defend against these kinds of claims.

⁸⁵ *Trade Secrets*, U.S. FOOD AND DRUG ADMINISTRATION, <http://www.fda.gov/AboutFDA/Transparency/PublicDisclosure/TradeSecrets/default.htm>.

⁸⁶ Redacting sensitive or confidential information submitted pursuant to actions involving the government is not new. For instance, Rule 345 (a) and (b) of the U.S. Tax Court Rules of Practice and Procedure allows whistleblowers reporting tax fraud to keep their names anonymous by petitioning the court via motion to do so. If the court deems it appropriate, identifying information related to the whistleblower can be redacted from the e-filings in such cases. U.S. T.C. R. PRAC. & P. 345 (a) and (b), http://ustaxcourt.gov/rules/amended_070612.pdf.

⁸⁷ *2015 DMCA Rulemaking*, Electr. Frontier Found., <http://www.eff.org/cases/2015-dmca-rulemaking> (last visited July 1, 2016).

E. *Recommendation #5: Require Better Oversight*

Our recommendations would also call for a mechanism to be put in place by the U.S. Copyright Office to ensure that accuracy reports filed by online platforms reflect reality. The U.S. Copyright Office is well suited to review and verify the data in question on an annual basis. It can also keep it confidential by redacting it from any Freedom of Information Act requests relating to it that are submitted by the public.

If the U.S. Copyright Office finds that system accuracy reports unduly and overoptimistically summarize the accuracy rates used to generate those reports, we propose that the companies be required to set aside a certain amount of money for a special fund created to finance the costs that users incur to defend themselves against illegitimate infringement suits. The fund would be similar to the recent fund created by YouTube to back users in such situations, but could be used to expand the program to reach a larger number of users being unduly accused of infringement. Currently, YouTube determines how to use these funds and for whom. We suggest that the U.S. Copyright Office function as a trustee for the fund. The U.S. Copyright Office should also serve on an advisory panel for the fund together with several small and large representatives from the content provider industry, as well as representatives from the creative community and their advocates. This will allow the U.S. Copyright Office to determine the criteria for who should be funded and how.

CONCLUSION

Copyright law allows songwriters to create new and innovative music by using prior work as long as the use transforms the original work in such a way that is in line with First Amendment considerations relating to critique, free speech, and artistic expression. This was illustrated by our case study of an indie songwriter, Elaine. However, under current algorithmic Content ID regimes, Elaine might be prevented from releasing her song online because some of its aspects match aspects of the GarageBand loop, Jennifer's traffic noise sound design, the civil rights anthem "We Shall Overcome," and Amir's TED Talk. Elaine would probably succeed in overturning this result if she were to go to court, but the cost to her and other creative artists in similar situations serves as a strong disincentive to doing so.

We recommend that online platforms be required to report the accuracy of their matches using the alternative metrics outlined in Part IV in order to create an incentive for online providers to reduce false positives that harm legitimate users of prior work. Further, we believe that a new layer of oversight by the U.S. Copyright Office will ensure that this takes place. Fines used to fund a program that covers the cost of user challenges to illegitimate take-down notices will provide further motivation for content providers asked to use and report on our proposed metrics for Content ID algorithm performance.

The use of algorithms by online platforms to assess copyright infringement is probably here to stay. Indeed, as recently as 2015, the Ninth Circuit Court of Appeals stated in the *Lenz* decision that “the implementation of computer algorithms appears to be a valid and good faith middle ground for processing a plethora of content while still meeting the DMCA’s requirements to somehow consider fair use.”⁸⁸ If adopted, our recommendations will further strengthen that middle ground by reducing the risks of false positives in music Content ID programs, thereby supporting the creation of new and innovative music.

⁸⁸ *Lenz*, 801 F.3d at 1135. The court further went on to say that Content ID algorithms were acceptable to use with respect to fair use considerations as long as (in cases such as the song composed by our case subject, Elaine) “the audio track matches the audio track of that same copyrighted work; and . . . nearly the entirety . . . is comprised of a single copyrighted work.” *Id.*

