

ORES: Facilitating re-mediation of Wikipedia's socio-technical problems

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Intelligent algorithms have a long history of making curation work in peer production tractable. From counter-vandalism to task routing, basic machine prediction allows open knowledge projects like Wikipedia to scale to the largest encyclopedia in the world. However, the ideologies and values of the community were captured in the development of these algorithms and the processes they support. Wikipedia's challenges and the community's values have changed in the last decade, but its algorithmic support systems have remained largely stagnant. The conversation about what quality control should be and what place algorithms have remains restricted to a few expert engineers. In this paper, we describe ORES: an algorithmic service designed to open up socio-technical conversations in Wikipedia to a broader set of participants. In this paper, we argue the theoretical mechanisms of social change ORES enables and we describe the phenomena around ORES from the 3 years since ORES' deployment.

CCS Concepts: • **Networks** → Online social networks; • **Computing methodologies** → Supervised learning by classification; • **Applied computing** → Sociology; • **Software and its engineering** → Software design techniques; • **Computer systems organization** → Cloud computing;

Additional Key Words and Phrases: Wikipedia, Reflection, Systems, Machine learning, Transparency, Fairness, Successor, Margin, Algorithms, Governance, Articulation

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1 INTRODUCTION

Wikipedia – the free encyclopedia that anyone can edit – faces many challenges in maintaining the quality of its articles and sustaining the volunteer community of editors. The people behind the hundreds of different language versions of Wikipedia have long relied on automation, bots, expert systems, recommender systems, human-in-the-loop assisted tools, and machine learning to help moderate and manage content at massive scales. The issues around artificial intelligence in Wikipedia are as complex as those facing other large-scale user-generated content platforms like Facebook, Twitter, or YouTube, as well as traditional corporate and governmental organizations that must make and manage decisions at scale. And like in those organizations, Wikipedia's automated classifiers are raising new and old issues about truth, power, responsibility, openness, and representation.

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Yet Wikipedia’s approach to AI has long been different than in the corporate or governmental contexts typically discussed in emerging fields like Fairness, Accountability, and Transparency in Machine Learning (FATML) or Critical Algorithms Studies (CAS). The volunteer community of editors has strong ideological principles of openness, decentralization, and consensus-based decision-making. The paid staff at the non-profit Wikimedia Foundation—which legally owns and operates the servers—are not tasked with making editorial decisions about content¹. This is instead the responsibility of the volunteer community, where a self-selected set of developers build tools, bots, and advance technologies in broad consultation with the community. Even though Wikipedia’s longstanding socio-technical system of algorithmic governance is far more open, transparent, and accountable than most platforms operating at Wikipedia’s scale, ORES, the system we present in this paper, pushes even further on the crucial issue of who is able to participate in the development and use of advance technologies.

ORES represents several innovations in openness in machine learning, particularly in seeing openness as a socio-technical challenge that is as much about scaffolding support as it is about open-sourcing code and data. With ORES, volunteers can curate labeled training data from a variety of sources for a particular purpose, commission the production of a machine classifier based on particular approaches and parameters, and make this classifier available via an API which anyone can query to score any edit to a page – operating in real time on the Wikimedia Foundation’s servers. Currently, 78 classifiers have been produced for 37 languages, classifying edits in real time on criteria like “damaging / not damaging”, “good faith / bad faith”, or an ordinal quality scale. ORES intentionally does not seek to produce a single classifier to enforce a gold standard of quality, nor does it prescribe particular ways in which scores and classifications will be incorporated into fully automated bots and semi-automated editing interfaces. Instead, ORES was built as a kind of cultural probe to support an open-ended set of community efforts to reimagine what machine learning in Wikipedia is and who it is for.

1.1 Audiences for this work

The issue of open participation in machine learning raises many issues that are widely relevant to both researchers of peer production platforms like Wikipedia, as well as those working across CSCW, social computing, machine learning, and critical algorithms studies.

To researchers of CSCW systems, this paper discusses the design and role of a technical system that supports a novel type of collaborative meta-work, as ORES makes it possible for volunteers commission the production of machine learning classifiers that other editors can use to support a variety of collaborative work practices in an established community of practice. In this paper, we detail this system’s design as it was built to align with the particular ways in which volunteers work in Wikipedia. We also describe how ORES has altered the meta-work of Wikimedia tool developers.

To the FATML/CAS communities, we are introducing an open-by-design advanced algorithmic platform that is widely used to maintain a critical information resource. This platform and its context implement several of the dominant recommendations for algorithmic system builders around transparency and community consent. Through the deployment of this system and subsequent design iterations, we are able to discuss novel practical considerations for what openness, accountability, and transparency mean in a large scale, real world system.

¹Except in rare cases, such as content that violates U.S. law, see <http://enwp.org/WP:OFFICE>

To algorithmic system-builders, we describe how we have approached key issues in developing a working, scalable, and robust system that matches the decentralized work practices of end-users in Wikipedia. Some of these approaches apply well described techniques (e.g. distributed processing and caching) while are novel strategies for giving tool developers and their users flexibility over how to use ORES's algorithmic predictions (e.g. model interrogation and threshold optimization).

At one level, ORES is widely relevant to researchers across social computing platforms, but it has specific relevance for researchers of commons-based peer production platforms like Wikipedia. ORES was created in the context of Wikipedia's much-discussed issues around newcomer socialization and inclusion. Wikipedia's existing algorithmic infrastructure for supporting various kinds of decision-making has generally been built by volunteers focused on quality control – removing spam, hate speech, vandalism, and low-quality content as soon as possible. Newcomer socialization has suffered from an apparent tradeoff as Wikipedians focused heavily on efficient quality management strategies[21, 22]. Peer production projects generally appear to struggle with balancing managing quality and participation[50], and automation in Wikipedia has generally made it more difficult for newcomers.

Past work has attempted to directly intervene by making tools[22] and designing spaces[33] that directly support newcomer socialization. While some of these interventions have shown promise[34], technological hurdles to change have prevented a systemic re-adjustment of the problematic aspects of quality control processes[22]. In this paper, we describe a novel system that represents a critical intervention in this space. ORES is an advanced algorithmic prediction service for Wikipedians that is designed to democratize the development of work process support tools to a wider audience. Unlike past work, our goal in the development of ORES is not to directly solve the quality/newcomer problem ourselves. Instead, we seek to remove barriers to others – to enable more people in the community of tool developers to experiment with novel strategies for managing quality and newcomer support.

1.2 Genre: A systems paper and a work study paper

This paper is a blend of two classic genres of CSCW scholarship, which reflects our dual intellectual lineages. Traditionally, systems papers introduce and implement a novel design. Because they make a new kind of abstract interaction possible, empirical evaluations of the system within the context of work practices are typically left for future work (e.g. [41]). In some ways, this paper follows this systems approach, in that we have produced a novel system and describe it with a thoughtful design rationale and technical specifications. But this paper also incorporates elements of a classic CSCW case study of work practices, which often point out how the abstract design rationales of a system did not align with the local context in which it was used (e.g. [48]). Our design rationale is deeply based on prior empirical and theoretical research into the specific practices of Wikipedia as a socio-technical system. Furthermore, our system serves as a kind of cultural probe in that we seek to elicit ideas about machine learning from our users, and we describe several case studies of the adoption of ORES and the reflective responses of our users.

By combining a situated design rationale, a description of the system, and case studies of work practices, this paper is mindful of issues long raised in HCI and CSCW around the gulf between systems developers, designers, and researchers (e.g. [8, 14, 17]). We follow the lead of contemporary CSCW researchers like Irani et al.[28] and provide a situated reflection of work practices and contexts in line with our system description. While this approach makes for a longer paper, it allows us to refer back to the ecological effects we hypothesize as part of our design rationale when discussing ORES' adoption patterns and our case studies.

In this paper, we first review related literature around open algorithmic systems, then discuss the socio-technical context of Wikipedia and the design rationale that lead us to building ORES. Next, we describe how we engineered the ORES system to match Wikipedian work practices – including innovations we’ve made with regards to algorithmic *openness* and *transparency*. Then we present a small set of case studies of interesting uses and critiques of ORES’ predictions. Finally, we conclude with a discussion of the issues raised by this work with our target audiences: CSCW researchers, FATML/CAS researchers, social-computing researchers, and algorithmic system-builders.

2 RELATED WORK

2.1 The politics of algorithms

Algorithmic systems play increasingly crucial roles in the governance of social processes [15]. In online spaces, these systems help us deal with information overload problems: What search results best balance *relevance* and *importance*? Which books are most *related* to the ones a user likes? In other spaces, algorithmic systems help institutions run more efficiently: Who is least *risky* to loan money to? Where should police patrol to encounter the most crime? Software algorithms are increasingly used in answering such questions that have no single right answer and where prior human decisions used as training data can be problematic [2, 51].

Algorithms designed to support work change work practices, shifting the dynamics of that work [6, 15, 57]. Software algorithms gain political relevance on par with other process-mediating artifacts (e.g. laws [31]). This increasing relevance of algorithms in social and political life renewed focus on questions of fairness and transparency².

There are repeated calls to address power dynamics at play in algorithmic bias through transparency and accountability of the algorithms that govern public life and access to resources [7][43][30]. The field around effective transparency and accountability mechanisms is growing. We cannot fully address the scale of concerns in this rapidly shifting, but we find inspiration in Kroll et al’s discussion of the potential and limitations of auditing and transparency. [30]

This paper discusses a specific political context (Wikipedia’s algorithmic quality control and socialization practices) and the development of novel algorithms for support of these processes. We implement an algorithmic intervention using the unusual strategy of deploying a set of prediction algorithms as a service, leaving decisions about appropriation to our users and other technology developers. Instead of seeking to train the single best classifier and implement it in our own designs, we embrace public auditing and re-interpretations of our model’s predictions as an *intended* and *desired* outcome. Extensive work on technical and social ways to achieve fairness and accountability generally do not discuss this kind of infrastructural intervention on communities of practice and their articulation work.

2.2 Machine prediction in support of open production

Open peer production systems have a long history of using machine learning in service of efficiency. For Wikipedia and related Wikimedia projects, vandalism detection and quality control has been paramount for practitioners and researchers. Article quality prediction models have also been explored and applied to help Wikipedians focus their work in the most beneficial places.

²See also <https://www.fatml.org/> for a conference devoted to these questions

Vandalism detection. The damage detection problem in Wikipedia is one of great scale. English Wikipedia receives about 160,000 new edits every day, which immediately go live without review. Wikipedians embrace this risk as the nature of an open encyclopedia, but work tirelessly to maintain quality. Every damaging or offensive edit puts the credibility of the community at risk, so all edits must be reviewed as soon as possible.

As an information overload problem, filtering strategies have been hugely successful in Wikipedia, and we briefly review a decade of work in this area. Potthast et al.’s seminal paper[40] describes a strategy using logistic regressions to automatically detecting vandalism. Jacobi described *ClueBot*[4], a Wikipedia editing bot deployed to automatically revert obvious vandalism. Adler et al. (2011) summarized the state of the art in feature extraction and modeling strategies, building a classifier that aggregated all features extraction strategies [1]. In some cases, researchers directly integrated their prediction models into tools for Wikipedians to use (e.g. STiki[56], a machine-supported human-computation tool). Yet most of this modeling work remains in the literature and has not been incorporated into current tools in Wikipedia.

Wikipedians have built and orchestrated a complex, multi-stage filter for incoming edits that is efficient and effective. Geiger & Halfaker quantitatively describe the temporal rhythm of edit review in Wikipedia[11]: First, automated bots revert vandalism that scores very highly according to a machine prediction model. Then “vandal fighters” use human-in-the-loop tools, where they review edits scored highly by machine prediction models, but not high enough for fully-automated reversion [13]. Edits that make it past these bots and “cyborgs” [23] are routed through a system of *watchlists*³ to experienced Wikipedia editors who are interested in the articles being edited. With this system in place, most damaging edits are reverted within seconds of when they are saved[11] and Wikipedia is kept clean.

Task routing. Task routing in Wikipedia is supported by a natural dynamic: people read what they are interested in, and when they see an opportunity to contribute, they do. This leads to a demand-driven contribution pattern where the most viewed content tends to be edited to the highest quality[27]. There are still many cases where Wikipedia remains misaligned[55], and content coverage biases creep in (e.g. for a long period of time, the coverage of Women Scientists in Wikipedia lagged far behind the rest of the encyclopedia[20]). By aligning interests with missed opportunities for contribution, these misalignments and gaps can be re-aligned and filled. Past work has explored collaborative recommender-based task routing strategies (see SuggestBot[5]) and shown good success. Recently, the maintainers of SuggestBot have developed article quality prediction models to help route attention to low quality articles[53]. Warncke-Wang and Halfaker have also used the article quality model to perform some one-off analyses to help Wikipedians critique and update their own manual quality assessments[54].

2.3 The Rise and Decline: Wikipedia’s socio-technical problems

While Wikipedians have made significant success in the algorithmic systems developed to support quality control, a line of critical research has studied the unintended consequences of this complex socio-technical system, particularly on newcomer socialization. [21][33][22]. In summary, Wikipedians struggled with the issues of scaling when the popularity of Wikipedia grew exponentially between 2005 and 2007[21]. In response, they developed quality control processes and technologies that prioritized efficiency by using machine prediction models[22] and templated warning messages[21]. This transformed newcomer socialization from a

³<http://enwp.org/:mw:Help:Watchlist>

primarily human and welcoming activity to one that is more dismissive and impersonal[33]. This is a good example of the values of the designers being captured in the process and supporting infrastructure they developed[22]. The efficiency of quality control work and the elimination of damage was considered extremely politically important, while the positive experience of newcomers was less politically important. The result was a sudden and sustained decline in the retention of good-faith newcomers and a decline in the overall population of Wikipedia editors[21].

After the effect of this trade-off was made clear, a number of initiatives were started in an effort to more effectively balance the needs for good community management with quality control efficiency. For example, a newcomer help space (The Teahouse[33]) was developed to provide a more welcoming and forgiving space for newcomers to ask questions and meet experienced Wikipedians. A newcomer training game was developed and tested with financial support from the Wikimedia Foundation[38]. The Wikimedia Foundation also formed a product development team that was tasked with making changes to Wikipedia’s user interfaces to increase newcomer retention⁴. Most of these efforts did not show gains in newcomer retention under experimental conditions. An exception is the Teahouse, where it was shown that intervening by inviting newcomers to participate in the question and answer space had a statistically significant benefit to long term newcomer retention[34].

Despite these targeted efforts and shifts in perception among some members of the Wikipedia community, the quality control process that was designed over a decade ago remains largely unchanged[22]. The quality control systems that were dominant before the publication of the seminal “Rise and Decline” study in 2013[21] remain dominant today. The regime of automatic reverting bots and semi-automated tools that conceptualize edits as “good” and “bad” remains in place and unchanged. Notably, Halfaker et al. experimented with developing a novel reversal of the damage detection tools by re-appropriating a damage detection model to highlight good editors who were running into trouble in the quality control system[22], but there has not been a significant shift in how quality control is enacted in Wikipedia.

3 DESIGN RATIONALE

In this section, we discuss systemic mechanisms behind Wikipedia’s socio-technical problems and how we as system builders make positive impact. Past work demonstrated how Wikipedia’s problems are systemic with no readily apparent system-level solutions. To responsibly use machine learning in addressing these problems, we examined how Wikipedia functions as a distributed system: how processes, policies, power, and software come together to make Wikipedia happen.

3.1 The context: Wikipedia as a genre ecology

Unlike traditional mass-scale projects, Wikipedia’s structure and processes are not centrally planned. Wikipedia’s system is a heterogeneous assemblage of humans, practices, policies, and software. This open system and its processes are dynamic, complex, and non-deterministic.

Genre ecologies is a theoretical framework we found useful in helping us account for the totality of factors and their relationships in Wikipedia, which is essential to building a system-level understanding of state and change processes. A genre ecology is “an interrelated group of genres (artifact types and the interpretive habits that have developed around them) used to jointly mediate the activities that allow people to accomplish complex objectives.”[47].

⁴<http://enwp.org/:m:Growthteam>

The genre ecology framework arose from observational research on how collaborators amend and repurpose existing officially-sanctioned tools — e.g. written documents, technological interfaces — and developed their own unofficial tools to supplement or circumvent official tools. This was needed in order to account for practical contingencies and emergent needs not anticipated, a longstanding concern in CSCW. In tracing the relationships among the set of official and unofficial tools used communities of practice, this literature helps conceptualize the relationships between tool genres and individual human actors, addressing issues of distributed agency, interdependency, rule formalization, and power dynamics in sociotechnical systems[46].

Morgan & Zachry used genre ecologies to characterize the relationships between Wikipedia’s official policies and “essays:” unofficial rules, best practices, and editing advice documents that are created by editors in order to contextualize, clarify, and contradict policies[35]. In Wikipedia, essays and policies co-exist and interact. For example, the “proper” interpretation of Wikipedia’s official Civility policy⁵ within a particular context may need to account for the guidance provided in related essays such as “No Angry Mastodons”⁶. In genre ecology terms, performing the work of enforcing civil behavior on Wikipedia is dynamically and contingently *mediated* by the guidance provided in the official policy and the guidance provided in any related essays. Unofficial genres provide interpretive flexibility in the application of official rules to local circumstances as well as challenging and re-interpreting official ideologies and objectives.

Algorithmic systems also have a role in mediating the policy, values, rules, and emergent practices in social spaces as well[31, 39, 49]. When looking at Wikipedia’s articulation work through the genre ecology lens, bots and human-computation tools mediate the meaning of policies and how Wikipedia enacts quality controls. For example, Sinebot enforces the signature policy in certain ways but not others[9], and the “Huggle” vandal fighting tool enacts quality in Wikipedia as a task of rapidly distinguishing good from bad edits in a live stream of recent changes[22]).

3.2 The problem: Wikipedia’s problems with automated mediation

As discussed in section 2, through the codevelopment of collaborative work processes and technologies to support them, Wikipedians traded soft, human newcomer socialization for hard, efficient quality control. Their software focused narrowly on most important problem to them — removing damage at all costs — and formalized processes that were previously more flexible and contingent. As they scaffolded their quality control workflows and values in code, other forms of quality control and socialization were pushed to the margins. The result was a marked decline in the retention of new editors in Wikipedia and a new threat to the core values of the project.

Where does change come from in a distributed cognition system that emerged based on community needs and volunteer priorities, where problematic assumptions have been embedded in the mediation of policy and the design of software for over a decade? Or maybe more generally, how does deep change take place in a genre ecology?

3.3 The complication: Making change in an decentralized ecology

As previously discussed, several initiatives were created to improve Wikipedian socialization practices, including the Teahouse and outreach efforts like Inspire Campaigns[32], which

⁵<http://enwp.org/WP:CIVIL>

⁶<http://enwp.org/WP:MASTODON>

elicited ideas from contributors on the margins of the community. However, the process of quality control has remained largely unchanged. This assemblage of mindsets, policies, practices, and software prioritizes quality/efficiency and does so effectively [11][22] but at a cost.

Instead of pursuing the tempting technical solutions to *just fix quality control*, it is not at all apparent what better quality control would look like. Even if we did, how does one cause systemic change in a decentralized system like Wikipedia? We draw from standpoint epistemology, specifically Harding and Haraway's concept of *successors*[25][26] in reflecting on the development of new software/process/policy components. Past work has explored developing a successor view that prioritizes the standpoints of mentors in support of new editors in Wikipedia, rather than the standpoints of vandal fighters focused on the efficiency of quality control[22][10]. However, a single point rarely changes the direction of an entire conversation or the shape of an entire ecology, so change is still elusive.

From these efforts, we know there is general interest in balancing quality/efficiency and diversity/welcomingness more effectively. So where are these designers who incorporate this expanded set of values? How to we help them bring forward their alternatives? How do we help them re-mediate Wikipedia's policies and values through their lens? How do we support the development of more successors?

3.4 The goal: Expanding the margins of the ecology

Successors come from the margin: they represent non-dominant values and engage in the re-mediation of articulation[37]. In our view, such successors are a primary means to change in an open genre ecology like Wikipedia. For anyone looking to enact a new view of quality control into the designs of a software system, there is a high barrier to entry: the development of a realtime machine prediction model. Without exception, all of the critical, high efficiency quality control systems that keep Wikipedia clean of vandalism and other damage employ a machine prediction model for highlighting the edits that are most likely to be bad. For example, Huggle⁷ and STiki⁸ use a machine prediction models to highlight likely damaging edits for human reviews. ClueBot NG⁹ uses a machine prediction model to automatically revert edits that are highly likely to be damaging. These automated tools and their users work to employ a multi-stage filter that quickly and efficiently addresses vandalism[11].

Wikipedians have long had extensive discussions and debates about the development of the thousands of relatively simple rule-based bots that are tasked with enforcing rules or supporting various tasks [9]. In contrast, there are high barriers to entry around machine learning classification models for quality control, both in knowing how they work and how to develop and operate them at Wikipedia's scale. Without these skills, it was not possible for the average Wikipedian to create an alternative view of what quality controls should be, while also accounting for efficiency and the need to scale. Notably, one of the key interventions in this area that did do so was also built by a computer scientist[22].

The result is a dominance of a certain type of individual: a computer scientist or software engineer with an eye towards improving the efficiency of quality control. This high barrier to entry and in-group effect has exacerbated the minimization of the margin and a supreme dominance of the authority of quality control regimes that were largely developed in 2006—long before the social costs of efficient quality control were understood[22]. Worse, this

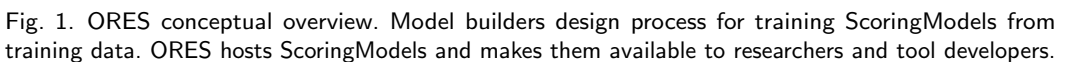
⁷<http://enwp.org/WP:Huggle>

⁸<http://enwp.org/WP:STiki>

⁹http://enwp.org/User:ClueBot_NG

Our approach: Lowering the barriers to entry. Wikipedia’s quality control processes are open to the development of successor systems for re-mediating quality control, but only for those with the right skills. We have two options for expanding the margins: (1) increase general literacy around machine classification techniques and operations at scale; or (2) minimize the need to deeply understand practical machine learning at scale in order to develop an effective quality control tool.

4 THE ORES SYSTEM



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4.1 Conceptual architecture

At the core, ORES is a collection of machine classifier models and an API. These models are designed and engineered by a varied set of model builders (some external researchers and others by our own research team) using varied sources of *training data*. The models that ORES hosts are engineered to support Wikipedian processes related to damage-detection, quality-assessment, and topic-routing, but the system is adaptable to a wide range of other models.

To make these models available for user, ORES implements a simple container service where the “container”, referred to as a *ScoringModel*, represents a fully trained and tested prediction model. All *ScoringModels* contain metadata about when the model was train/tested and which features are necessary for making a prediction. All predictions take the form of a JSON document. The ORES service provides access to *ScoringModels* via a RESTful HTTP interface and serves the predictions (JSON documents) to users. We chose this service structure because Wikimedian tool developers (our target audience) are familiar with this RESTful API/JSON workflow due to the dominant use of the MediaWiki API among tool developers. See sections A.1.1 and ?? for details and examples of about ORES’ outputs.

4.2 Scaling & robustness

To be useful for Wikipedians and tool developers, ORES uses distributed computation strategies to provide a robust, fast, high-availability service. Reliability is a critical concern in Wikipedian quality control work. Interruptions in Wikipedia’s algorithmic systems have historically led to increased burdens for human workers and a higher likelihood that readers will see vandalism[11]. As previously discussed, we wanted to support Wikipedians who did not have the access and ability to operate a machine learning classifier at datacenter scales. The widespread use of ORES for multiple models across language versions of Wikimedia wikis could potentially involve orders of magnitude more computation than has ever been used for machine learning in Wikipedia.

This horizontal scalability is achieved in two ways: input-output (IO) workers (uwsgi¹⁰) and the computation (CPU) workers (celery¹¹). Requests are split across available IO workers, and all necessary data is gathered using external APIs (e.g. the MediaWiki API¹²). The data is then split into a job queue managed by *celery* for the CPU-intensive work. This efficiently uses available resources and can dynamically scale, adding and removing new IO and CPU workers in multiple datacenters as needed. This is also fault-tolerant, as servers can fail without failing the service as a whole.

4.3 Real-time processing

The most common use case of ORES is real-time processing of edits. For example, those using counter-vandalism tools like Huggle monitor edits within seconds of when they are made. It is critical that ORES return these requests return in a timely manner. We implement several strategies to optimize this request pattern.

Single score speed. In the worst case scenario, ORES is generating a score from scratch. This is the common case when a score is requested in real-time—which invariably occurs right after the target edit or article is saved. We work to ensure that the median score duration is around 1 second. Our metrics tracking currently suggests that for the week April

¹⁰<https://uwsgi-docs.readthedocs.io/>

¹¹<http://www.celeryproject.org/>

¹²<http://enwp.org/:mw:MW:API>

6-13th, our median, 75%, and 95% score response timings are 1.1, 1.2, and 1.9 seconds respectively.

Caching and precaching. In order to take advantage of our users' overlapping interests in scoring recent activity, we also maintain a basic least-recently-used (LRU) cache¹³ using a deterministic score naming scheme (e.g. `enwiki:123456:damaging` would represent a score needed for the English Wikipedia damaging model for the edit identified by 123456). This allows requests for scores that have recently been generated to be returned within about 50ms via HTTPS. In other words, a request for a recent edit that had previously been scored is 20X faster due to this cache.

In order to make sure that scores for *all recent edits* are available in the cache for real-time use cases, we implement a “precaching” strategy that listens to a high-speed stream of recent activity in Wikipedia and automatically requests scores for a specific subset of actions (e.g. edits). With our LRU and pre-caching strategy, we attain a cache hit rate of about 80% consistently.

De-duplication. In real-time ORES use cases, it's common to receive many requests to score the same edit/article right after it was saved. We use the same deterministic score naming scheme from the cache to identify scoring tasks, and ensure that simultaneous requests for that same score attach to the same result (or pending result) rather than starting a duplicate scoring job. This pattern is very advantageous in the case of precaching, because of our network latency advantage: we can generally guarantee that the precaching request for a specific score precedes the external request for a score. All waiting requests attach to the result of a single score generation process that starts prior to receiving the external request. So even in worst-case scenarios where we're still calculating scores, we often see a better-than-expected response speed from the tool user's point of view.

4.4 Batch processing

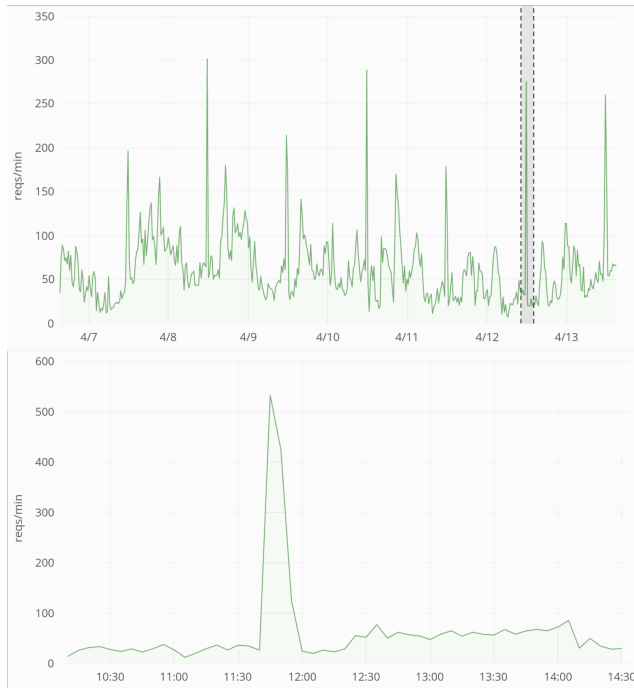
Many different types of Wikipedia's bots rely on batch processing strategies to support Wikipedia work processes[9], so ORES needs to support sudden, high-intensity querying. For example, many bots are designed to build worklists for Wikipedia editors (e.g. [5]) and recently, many of them have adopted ORES to include an article quality prediction for use in prioritization (see section 6). Work lists are either built from the sum total of all 5m+ articles in Wikipedia, or from some large subset specific to a single WikiProject (e.g. WikiProject Women Scientists claims about 6k articles¹⁴). We've observed robots submitting large batch processing jobs to ORES once per day. It's relevant to note that many researchers are also making use of ORES for various analyses, and their activity usually shows up in our logs as a similar burst of requests.

In order to most efficiently support this type of querying activity, we implemented batch optimizations in ORES by splitting IO and CPU operations into distinct stages. During the IO stage, all data is gathered to generate a set of scores. During the CPU stage, scoring jobs are split across our distributed processing system. This batch processing affords up to a 5X increase in time to scoring speed for large requests[44]. At this rate, a user can score 1 million revisions in less than 24 hours in the worst case scenario (no scores were cached)—which is unlikely for recent Wikipedia activity.

¹³Implemented natively by Redis, <https://redis.io>

¹⁴As demonstrated by <https://quarry.wmflabs.org/query/14033>

4.5 Empirical access patterns



(a) External requests per minute with a 4 hour block broken out to highlight a sudden burst of requests.



(b) Precaching requests per minute

Fig. 2. Request rates to the ORES service for the week ending on April 13th, 2018

The ORES service has been online since July 2015[24]. Since then, usage has steadily risen as we’ve develop and deploy new models, and additional integrations are made by tool developers and researchers. Currently, ORES supports 78 different models and 37 different language-specific wikis.

Generally, we see 50 to 125 requests per minute from external tools that are using ORES’ predictions (excluding the MediaWiki extension that is more difficult to track). Sometimes these external requests will burst up to 400-500 requests per second. Figure 2a shows the periodic and bursty nature of scoring requests received by the ORES service. Note that

every day at about 11:40 UTC, the request rate jumps—most likely a batch scoring job such as a bot.

Figure 2b shows our rate of precaching requests coming from our own systems. This graph roughly reflects the rate of edits that are happening to all of the wikis that we support since we’ll start a scoring job for nearly every edit as it happens. Note that the number of precaching requests is about an order of magnitude higher than our known external score request rate. This is expected, since Wikipedia editors and the tools they use will not request a score for every single revision. This is a computational price we pay to attain a high cache hit rate and to ensure that our users get the quickest possible response for the scores that they *do* need.

Taken together these strategies allow us to optimize the real-time quality control workflows and batch processing jobs of Wikipedians and their tools. Without serious effort to make sure that ORES is practically fast and highly available to real-time use cases, ORES would become irrelevant to the target audience and thus irrelevant as a work-support infrastructure. By engineering a system that conforms to the work-process needs of Wikipedians and their tools, we’ve built a system intervention that has the potential gain wide adoption in Wikipedia’s technical ecology.

5 INNOVATIONS IN OPENNESS

Our goals in the development of ORES and the deployment of models is to keep the process—the flow of data from random samples through model training and evaluation—open for review, critique, and iteration. In this section, we’ll describe how we implemented transparent reproducibility in our model development process, and how ORES outputs a wealth of useful and nuanced information for users. By making this detailed information available to users and developers, we hope to enable flexibility and power in the evaluation and use of ORES predictions for novel purposes. In this section, we describe some of the key, novel innovations that have made ORES fit Wikipedian concerns and be flexible to re-use. The appendix also contains information about ORES’ detailed prediction output (section A.1.1), how users and tools can adjust their use to model fitness (section A.1.2, and how the whole model development workflow is made inspectable and replicable (section A.1.3).

5.1 Collaboratively labeled data

There are two primary strategies for gathering labeled data for ORES’ models: found traces and manual labels.

Found traces. For many models, there are already a rich set of digital traces that can be assumed to reflect a useful human judgement. For example, in Wikipedia, it’s very common that damaging edits will be reverted and that good edits will not be reverted. Thus the revert action (and remaining traces) can be used to assume that the reverted edit is damaging. We have developed a re-usable script¹⁵ that when given a sample of edits, will label the edits as “reverted_for_damage” or not based on a set of constraints: edit was reverted within 48 hours, the reverting editor was not the same person, and the edit was not restored by another editor.

However, this “reverted_for_damage” label is problematic in that many edits are reverted not because they are damaging but because they are involved in some content dispute. Also, the label does not differentiate damage that is a good-faith mistake from damage that is

¹⁵see *autolabel* in <https://github.com/wiki-ai/editquality>

intentional vandalism. So in the case of damage prediction models, we'll only make use of the “reverted_for_damage” label when manually labeled data is not available.

Another case of found traces is article quality assessments—named “wp10” after the Wikipedia 1.0 assessment where the article quality assessment scale originated¹⁶. We follow the process developed by Warncke-Wang et al.[52] to extract the revision of an article that was current at the time of an assessment. Many other wikis employ a similar process of article quality labeling (e.g. French Wikipedia and Russian Wikipedia), so we can use the same script to extract their assessments with some localization¹⁷. However other wikis either do not apply the same labeling scheme consistently or at all and manual labeling is our only option.

Manual labeling. We hold manual labeling as the gold standard for purposes of training a model to replicate human judgement. By asking Wikipedians to demonstrate their judgement on examples from their own wikis, we can most closely tailor model predictions to match the judgements that make sense to these communities. This contrasts with found data that is much easier to come by as it is available but the implicit signals may not exactly match the intended use of the model. Manual labeling has a high up-front expense of human labor. In order to efficiently utilize valuable time investments by our collaborators, mostly volunteer Wikipedians, we've developed a system called “Wiki Labels”¹⁸. Wiki Labels allows Wikipedians to submit judgments of specific random samples of Wiki content using a convenient interface and logging in via their Wikipedia account.

For example, to supplement our models of edit quality, we replace the models based on found “reverted_for_damage” traces with manual judgments where we specifically ask labelers to distinguish “damaging”/good from “good-faith”/vandalism. Using these labels we can build two separate models which allow users to filter for edits that are likely to be good-faith mistakes[19], to just focus on vandalism, or to apply themselves broadly to all damaging edits.

5.2 Threshold optimization

When we first started developing ORES, we realized that operational concerns of Wikipedia's curators need to be translated into confidence thresholds for the prediction models. For example, counter-vandalism patrollers seek catch all (or almost all) vandalism before it is allowed to stick in Wikipedia for very long. That means they have an operational concern around the *recall* of a damage prediction model. They'd also like to review as few edits as possible in order to catch that vandalism. So they have an operational concern around the *filter rate*—the proportion of edits that are not flagged for review by the model[18].

By finding the threshold of prediction likelihood that optimizes the filter-rate at a high level of recall, we can provide vandal-fighters with an effective trade-off for supporting their work. We refer to these optimizations in ORES as *threshold optimizations* and ORES provides information about these thresholds in a machine-readable format so that tools can automatically detect the relevant thresholds for their wiki/model context.

Originally, when we developed ORES, we defined these threshold optimizations in our deployment configuration. But eventually, it became apparent that our users wanted to be able to search through fitness metrics to choose thresholds that matched their own operational concerns. Adding new optimizations and redeploying quickly became a burden on us and a

¹⁶<http://enwp.org/WP:WP10>

¹⁷see *extract_labelings* in <https://github.com/wiki-ai/articlequality>

¹⁸<http://enwp.org/m:Wikilabels>

delay for our users. So we developed a syntax for requesting an optimization from ORES in realtime using fitness statistics from the models tests. E.g. `maximum recall @ precision >= 0.9` gets a useful threshold for a counter-vandalism bot or `maximum filter_rate @ recall >= 0.75` gets a useful threshold for semi-automated edit review (with human judgement).

```
{"threshold": 0.30, ...,
  "filter_rate": 0.88, "fpr": 0.097, "precision": 0.21, "recall": 0.75}
```

Fig. 3. Result of https://ores.wikimedia.org/v3/scores/enwiki/?models=damaging&model_info=statistics.thresholds.true.'maximumfilter_rate@recall'=0.75

This result shows that, when a threshold is set on 0.299 likelihood of `damaging=true`, then you can expect to get a recall of 0.751, precision of 0.215, and a filter-rate of 0.88. While the precision is low, this threshold reduces the overall workload of vandal-fighters by 88% while still catching 75% of (the most egregious) damaging edits.

5.3 Dependency injection and interrogability

From a technical perspective, ORES is a algorithmic “scorer” container system. It’s primarily designed for hosting machine classifiers, but it is suited to other scoring paradigms as well. E.g. at one point, our experimental installation of ORES hosted a Flesch-Kincaid readability scorer. The only real constraints are that the scorer must express its inputs in terms of “dependencies” that ORES knows how to solve and the scores must be presentable in JSON (Javascript Object Notation).

5.3.1 Dependency injection. One of the key features of ORES that allows scores to be generated in an efficient and flexible way is a dependency injection framework.

Efficiency. For example, there are several features that go into the “damaging” prediction model that are drawn from the *diff* of two versions of an articles text (words added, words removed, badwords added, etc.) Because all of these features “depend” on the *diff*, the dependency solver can make sure that only one *diff* is generated and that all subsequent features make use of that shared data.

ORES can serve multiple scores in the same request. E.g. a user might want to gather a set of scores: “edit type”, “damaging”, and “good-faith”. Again, all of these prediction models depend on features related to the edit *diff*. ORES can safely combine all of the features required for each of the requested models and extract them with their shared dependencies together. Given that feature extraction tends to take the majority of time in a real-time request request (partially for fetching data [IO], partially for computation time [CPU]), this allows the scoring for multiple, similar models to take roughly the same amount of time as scoring a single model.

Flexibility. When developing a model, it’s common to experiment with different feature sets. A natural progression in the life of a model in the wild involves the slow addition of new features that prove useful during experimentation. By implementing a dependency system and a dependency solver, a model can communicate to ORES which features it needs and ORES can provide those features. At no point does a model developer need to teach ORES how to gather new data. All of the information needed for the solver to solve any given feature set is wrapped up in the dependencies.

5.3.2 Interrogability. The flexibility provided by the dependency injection framework let us implement a novel strategy for exploring *how* ORES' models make predictions. By exposing the features extracted to ORES users and allowing them to inject their own features, we can allow users to ask how predictions would change if the world were different. Let's say you wanted to explore how ORES judges unregistered (anon) editors differently from registered editors. Figure 4 demonstrates two prediction requests to ORES.

<pre>"damaging": { "score": { "prediction": false, "probability": { "false": 0.938910157824447, "true": 0.06108984217555305 } } }</pre>	<pre>"damaging": { "score": { "prediction": false, "probability": { "false": 0.9124151990561908, "true": 0.0875848009438092 } } }</pre>
---	---

(a) Prediction with anon = false injected

(b) Prediction with anon = true injected

Fig. 4. Two “damaging” predictions about the same edit are listed for ORES. In one case, ORES is asked to make a prediction assuming the editor is unregistered (anon) and in the other, ORES is asked to assume the editor is registered.

Figure 4a shows that ORES’ “damaging” model concludes that the edit identified by the *revision ID* of 34234210 is not damaging with 93.9% confidence. We can ask ORES to make a prediction about the exact same edit, but to assume that the editor was unregistered (anon). Figure 4b shows the prediction if edit were saved by an anonymous editor. ORES would still conclude that the edit was not damaging, but with less confidence (91.2%). By following a pattern like this for a single edit or a set of edits, we can get to know how ORES prediction models account for anonymity.

This is a very powerful tool for examining the potential biases in judgement. Imagine being able to ask a law enforcement officer if they feel like they have probable cause for a search and then asking again how their answer would change if the suspect were black.

Interrogability isn’t only useful for checking to see where ORES’ biases originate and what effects they have on predictions. For example, Ross has started using our article quality prediction models (*wp10*) as a method for suggesting work to new editors¹⁹. By asking ORES to score a student’s draft and then asking ORES to reconsider the predicted quality level of the article with *one more header*, *one more image*, or *one more citation*, he’s built an intelligent user interface that can exposes the internal structure of a model in order to recommend the most productive development to the article—the change that will most likely bring it to a higher quality level.

6 ADOPTION PATTERNS

When we designed and developed ORES, we were targeting a specific problem—expanding the set values applied to the design of quality control tools to include recent a recent understanding of the importance of newcomer socialization. We don’t have any direct control of how developers chose to use ORES. We hypothesize that, by making edit quality

¹⁹<https://dashboard-testing.wikiedu.org>

predictions available to all developers, we would lower the barrier to experimentation in this space. It's clear that we lowered barriers to experimentation. After we deployed ORES, we implemented some basic tools to showcase ORES, but we observed a steady adoption of our various prediction models by external developers in current tools and through the development of new tools²⁰.

6.1 Showcase tools

In order to showcase the utility of ORES, we developed a two simple tools to surface ORES predictions within MediaWiki—the wiki that powers Wikipedia: *ScoredRevisions* and the *ORES Review Tool*.

ScoredRevisions²¹ is a javascript-based “gadget” that runs on top of MediaWiki. When certain pages load in the MediaWiki interface (E.g. Special:RecentChanges, Special:Watchlist, etc.), the ScoredRevisions submits requests to the ORES service to score the edits present on the page. The javascript then updates the page with highlighting based on ORES predictions. Edits that are likely to be “damaging” are highlighted in red. Edits that might be damaging and are worth reviewing are highlighted in yellow. Other edits are left with the default background.

While this interface was excellent for displaying ORES potential, it had limited utility. First, it was severely limited by the performance of the ORES system. While ORES is reasonably fast for scoring a single edit, scoring 50-500 edits (the ranges that commonly appear on these pages) can take 30 seconds to 2 minutes. So a user is left waiting for the highlighting to appear. Because ScoredRevisions is only able to score edits after they are rendered, there was no way for a user to ask the system to filter edits ahead of time to only show edits that are likely to be damaging. The user needed to visually filter the long lists based on highlighted rows.

The ORES Review Tool²² is a MediaWiki extension implemented in PHP. It uses an offline process to score all recent edits to Wikipedia and to store those scores in a table for querying and quick access. This tool implemented similar functionality to *ScoredRevisions* but because it had pre-cached ORES scores in a table, it rendered highlights for likely damaging edits as soon as the page loaded. It enabled users to filter based on likely damaging edits.

We released the ORES Review Tool as a “beta feature” on Wikimedia wikis where we were able to develop advanced edit quality models. The response was extremely positive. Over 26k editors in Wikipedia had manually enabled the ORES Review Tool by April of 2017. For reference, the total number of active editors across all languages of Wikipedia varies around 70k²³, so this means that about a 3rd of active editors consciously chose to enable the feature.

6.2 Adoption in current tools

Many tools for counter-vandalism in Wikipedia were already available when we developed ORES. Some of them made use of machine prediction (e.g. Huggle²⁴, STiki, ClueBot NG), but most did not. Soon after we deployed ORES, many developers that had not previously included their own prediction models in their tools were quick to adopt ORES. For example,

²⁰See complete list: <http://enwp.org/:mw:ORES/Applications>

²¹<https://github.com/he7d3r/mw-gadget-ScoredRevisions>

²²http://enwp.org/:mw:ORES_review_tool

²³<https://stats.wikimedia.org/EN/TablesWikipediansEditsGt5.htm>

²⁴Notably, Huggle adopted ORES prediction models soon after we deployed

RealTime Recent Changes²⁵ includes ORES predictions along-side their realtime interface and FastButtons²⁶, a Portuguese Wikipedia gadget, began displaying ORES predictions next to their buttons for quick reviewing and reverting damaging edits.

Other tools that were not targeted at counter-vandalism also found ORES predictions—specific that of *article quality* (wp10)—useful. For example, RATER²⁷, a gadget for supporting the assessment of article quality began to include ORES predictions to help their users assess the quality of articles and SuggestBot²⁸[5], a robot for suggesting articles to an editor, began including ORES predictions in their tables of recommendations.

6.3 Development of new tools

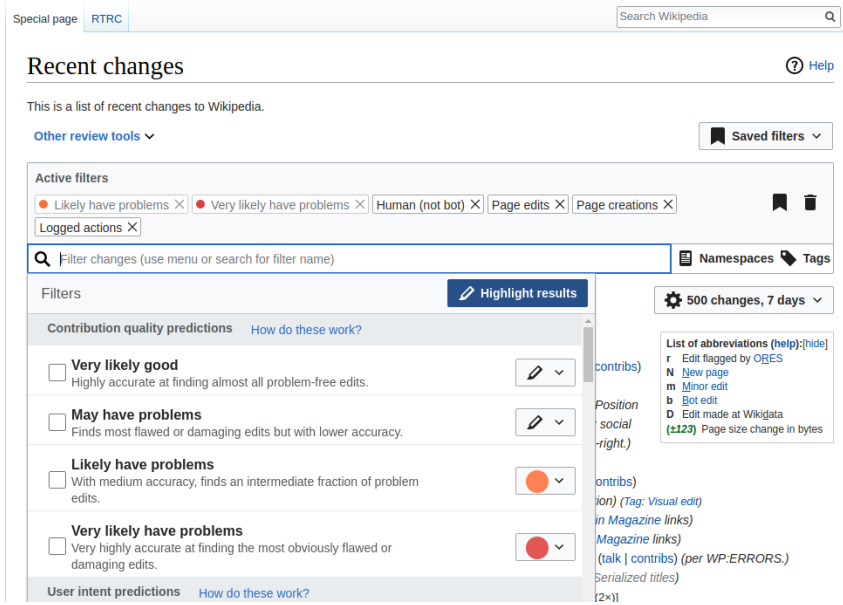


Fig. 5. A screenshot of the Edit Review Filters interface with ORES score-based filters

Many new tools have been developed since ORES has released that may not have been developed at all otherwise. For example, the Wikimedia Foundation product department developed a complete redesign on MediaWiki’s Special:RecentChanges interface that implements a set of powerful filters and highlighting. They took the ORES Review Tool to it’s logical conclusion with an initiative that they referred to as Edit Review Filters²⁹. In this interface, ORES scores are prominently featured at the top of the list of available features, and they have been highlighted as one of the main benefits of the new interface to the editing community.

When we first developed ORES, English Wikipedia was the only wiki that we are aware of that had a robot that used machine prediction to automatically revert obvious vandalism[4].

²⁵<http://enwp.org/:m:RTRC>

²⁶<http://enwp.org/:pt:Wikipedia:Scripts/FastButtons>

²⁷<http://enwp.org/::en:WP:RATER>

²⁸<http://enwp.org/User:SuggestBot>

²⁹http://enwp.org/:mw:Edit_Review_Improvements

After we deployed ORES, several wikis developed bots of their own to use ORES predictions to automatically revert vandalism. For example, in PatruBOT in Spanish Wikipedia³⁰ and Dexbot in Persian Wikipedia³¹ now automatically revert edits that ORES predicts are damaging with high confidence. These bots have been received with mixed acceptance. Because of the lack of human oversight, concerns were raised about PatruBOT's false positive rate but after consulting with the developer, we were able to help them find an acceptable threshold of confidence for auto-reverts.

One of the most noteworthy new tools is the suite of tools developed by Sage Ross to support the Wiki Education Foundation's³² activities. Their organization supports classroom activities that involve editing Wikipedia. They develop tools and dashboards that help students contribute successfully and to help teachers monitor their students' work. Ross has recently published about how they interpret meaning from ORES' article quality models^[42] and has integrate this prediction into their tools and dashboards to recommend work that students need to do to bring their articles up to Wikipedia's standards. See our discussion of interrogation in Section 5.

7 CASE STUDIES IN REFLECTION

When we first deployed ORES, we reached out to several different wiki-communities and invited them to test out the system for use in patrolling for vandalism. In these announcements, we encouraged editors to install ScoredRevisions, the only tool that used made use of ORES' edit quality models at the time. ScoredRevisions both highlights edits that are likely to be damaging (as predicted by the model) and displays the likelihood of the prediction as a percentage.

Before long, our users began filing false-positive reports on wiki pages of their own design. In this section we will describe three cases where our users independently developed these false-positive reporting pages and how they used them to understand ORES, the roles of automated quality control in their own spaces, and to communicate with us.

7.1 Report mistakes (Wikidata)

Improvements [\[edit \]](#)

Diff id	✦	Damaging	✦	Old score	✦	Score1	✦	Score2	✦	Score3	✦	1st improv.	✦	2nd	✦	3rd	✦	Overall	✦
210649590		No		91%		30%		5%		0%		+61%		+25%		+5%		+91%	
237999679		No		84%		71%		63%		60%		+13%		+8%		+3%		+24%	
243937491		No		95%		46%		74%		71%		+49%		-28%		+3%		+24%	
251530750		No		91%		55%		56%		55%		+36%		-1%		+1%		+36%	
253584599		No		99%		89%		78%		70%		+10%		+11%		+8%		+29%	
257856652		No		91%		30%		4%		1%		+61%		+26%		+3%		+90%	

Fig. 6. A slice of the ORES report mistakes table in Wikidata.

When we first deployed prediction models for Wikidata, a free and open knowledge base that can be read and edited by both humans and machines³³, we were breaking new ground by building a damage detection classifier based on a structured data wiki^[44]. So we created a

³⁰<https://es.wikipedia.org/wiki/Usuario:PatruBOT>

³¹<https://fa.wikipedia.org/wiki/User:Dexbot>

³²<https://wikiedu.org/>

³³<https://wikidata.org>

page called “Report mistakes” and invited users to tell us about mistakes that the prediction model made on that page. We left the format and structure largely up to the users.

Within 20 minutes, we received our first report from User:Mbch that ORES was reporting edits that couldn’t possibly be vandalism as potentially damaging. As reports streamed in, we began to respond to them and make adjustments to the model building process to address data extraction bugs and to increase the signal so that the model differentiate damage from non-damaging edits. After a month of reports and bug fixes, we decided to build a table to represent the progress that we made in iterations on the model against the reported false-positives. See Figure 6 for a screenshot of the table. Each row represents a mis-classified edit, and each column describes the progress we made in not detecting those edits as damaging in future iterations of the model. Through this process, we learned how Wikidata editors saw damage and how our modeling and feature extraction process captured signals in ways that differed from Wikidata editors’ understandings. We were also able to publicly demonstrate improvements to this community.

7.2 Patrolling/ORES (Italian Wikipedia)

Italian Wikipedia was one of the first wikis where we deployed basic edit quality models. Our local collaborator who helped us develop the language specific features, User:Rotpunkt, created a page for ORES³⁴ with a section for reporting false-positives (“falsi positivi”). Within several hours, Rotpunkt and a few other edits started to notice some trends in their false positive reports. First, Rotpunkt noticed that there were several counter-vandalism edits that ORES was flagging as potentially damaging, so he made a section for collecting that specific type of mistake (“annullamenti di vandalismo”). A few reports later and he added a section for “corrections to the verb for *have*” (“correzioni verbo avere”). Through this process, editors from Italian Wikipedia were essentially performing a grounded theory exploration of the general classes of errors that ORES was making.

Once there were several of these mistake-type sections and several reports within each section, Rotpunkt reached out to us to let us know what he had found. He explained to us (via our IRC channel) that many of ORES mistakes were understandable, but there were some general trends in mistakes around the Italian verb for *have*: “ha”. We knew immediately what was likely to be the issue. It turns out that “ha” in English and many other languages is laughing, an example of informal language that doesn’t belong in an encyclopedia article. While the word “ha” in Italian translates to “have” and is perfectly acceptable in articles.

Because of the work of Rotpunkt and his collaborators in Italian Wikipedia, we were able to recognize the source of this issue (a set of features intended to detect the use of *informal language* in articles) and to remove “ha” from that list for Italian Wikipedia. This is just one example of many issues we were able to address because of the grounded theory and thematic analysis performed by Italian Wikipedians.

7.3 PatruBOT (Spanish Wikipedia)

Soon after we released support for Spanish Wikipedia, User:jem developed a robot to automatically revert damaging edits using ORES predictions (PatruBOT). This robot was not running for long before our discussion pages started to be bombarded with confused Spanish-speaking editors asking us questions about why ORES did not like their work. We

³⁴<https://it.wikipedia.org/wiki/Progetto:Patrolling/ORES>

struggled to understand the origin of the complaints until someone reached out to us to tell us about PatruBOT and its activities.

We haven't been able to find the source code for PatruBot, but from what we've been able to gather looking at its activity, it appears to us that PatruBOT was too sensitive and was likely reverting edits that ORES did not have enough confidence about. Generally, when running an automated counter-vandalism bot, the most immediately operational concern is around *precision* (the proportion of positive predictions that are true-positives). This is because mistakes are extra expensive when there's no human judgement between a prediction and a revert (rejection of the contribution). The proportion of all damaging edits that are actually caught by the bot (*recall*) is a secondary concern to be optimized.

We recommend that bot developers who are interested in running an automated counter-vandalism bot use a threshold that maximizes recall at high precision (90% is a good starting point). According to our queries³⁵, the Spanish Wikipedia damaging model can be expected to have 90% precision and catch 17% of damage if the bot only reverted edits where the likelihood estimate is above 0.959.

We reached out to the bot developer to try to help, but given the voluntary nature of their work, they were not available to discuss the issue with us. Eventually, other editors who were concerned with PatruBOT's behavior organized an informal crowdsourced evaluation of the fitness of PatruBOT's behavior³⁶ where they randomly sampled 1000 reverts performed by PatruBOT and reviewed their appropriateness. At the time of writing, PatruBOT has been stopped³⁷ and the informal evaluation is ongoing.

7.4 Bias against anonymous editors

Shortly after we deployed ORES, we started receiving reports that ORES' damage detection models were overly biased against anonymous editors. At the time, we were using Linear SVM³⁸ estimators to build classifiers, and we were considering making the transition towards ensemble strategies like GradientBoosting and RandomForest estimators³⁹. We took the opportunity to look for bias in the error of estimation between anonymous editors, newly registered editors. By using our feature injection/interrogation strategy (described in Section 5), we could ask our current prediction models how they would change their predictions if the exact same edit were made by a different editor.

Figure 7 shows the probability density of the likelihood of "damaging" given three different passes over the exact same test set using two of our modeling strategies. Figure 7a shows that, when we leave the features to their natural values, it appears that both models are able to differentiate effectively between damaging edits (high damaging probability) and non-damaging edits (low damaging probability) with the odd exception of a large amount of non-damaging edits with a relatively high damaging probability around 0.8 in the case of the Linear SVM model. Figures 7b and 7c show a stark difference. For the scores that go into these plots, characteristics of anonymous editors and newly registered editors were injected for all of the test edits. We can see that the GradientBoosting model can still differentiate

³⁵https://ores.wikimedia.org/v3/scores/eswiki?models=damaging&model_info=statistics.thresholds.true.%27maximum%20recall%20@%20precision%20%3E=%200.9%27

³⁶https://es.wikipedia.org/wiki/Wikipedia:Mantenimiento/Revisi%C3%B3n_de_errores_de_PatruBOT%2FAn%C3%A1lisis

³⁷https://es.wikipedia.org/wiki/Wikipedia:Caf%C3%A9%2FArchivo%2FMiscel%C3%A1nea%2FActual#Parada_de_PatruBOT

³⁸<http://scikit-learn.org/stable/modules/generated/sklearn.svm.LinearSVC.html>

³⁹<http://scikit-learn.org/stable/modules/ensemble.html>

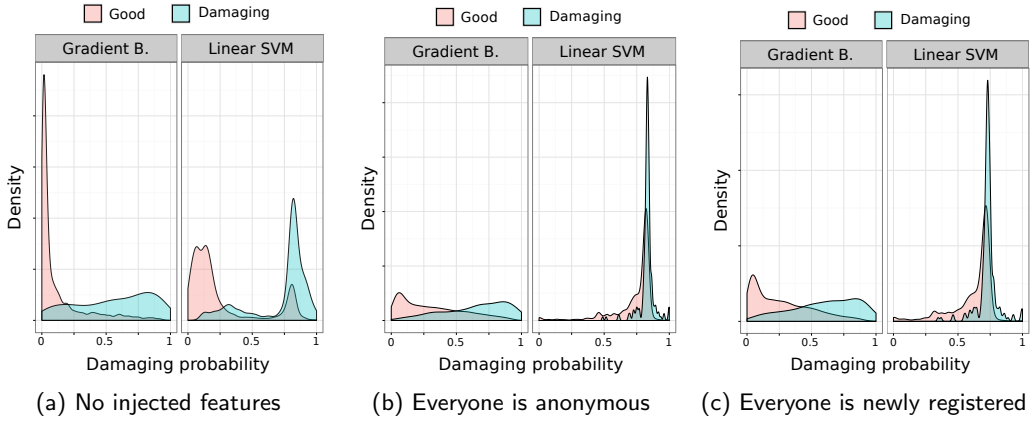


Fig. 7. The distributions of the probability of a single edit being scored as “damaging” based on injected features for the target user-class is presented. Note that when injecting user-class features (anon, newcomer), all other features are held constant.

damage from non-damage while the Linear SVM model flags nearly all edits as damage in both case.

Through the reporting of this issue and our subsequent analysis, we were able to identify the issue and show that an improvement to our modeling strategy mitigates the problem. Without such a tight feedback loop, we most likely wouldn’t have noticed how poorly ORES’ damage detection models were performing in practice. Worse, it might have caused vandal-fighters to be increasingly (and inappropriately) skeptical of contributions by anonymous editors and newly registered editors—two groups of contributors that are already met with unnecessary hostility⁴⁰[21].

7.5 Discussion

These case studies in responses to ORES provide a window into how our team has been able to work with the locals in various communities to refine our understandings of their needs, into methods for recognizing and addressing biases in ORES’ models, and into how people think about what types of automation they find acceptable in their *spaces*.

Refining our understandings and iterating our models. The information divide between us researchers/engineers and those members of a community is often wider than we realize. Through iteration with the Wikidata and Italian models, we learned about incorrect assumptions we would make about how edits happen (e.g. client edits in Wikidata) and how language works (e.g. “ha” is not laughing in Italian). It’s likely we would never be able to fully understand the context in which damage detection models should operate before deploying the models. But these case studies demonstrate how, with a tight communication loop, many surprising and wrong assumptions that were baked into our modeling process could be identified and addressed quickly. It seems that many of the relevant issues in feature engineering and model tuning become apparent when the model is used in context to try to address a real problem (in these cases, counter-vandalism).

⁴⁰http://enwp.org/:en:Wikipedia:IPs_are_human_too

Methods for recognizing and addressing bias. The Italian Wikipedians showed us something surprising and interesting about collaborative evaluation of machine prediction: thematic analysis is very powerful. Through the collection of ORES mistakes and iteration, our Italian collaborators helped us understand general trends in the types of mistakes that ORES made. It strikes us that this is a somewhat general strategy for bias detection. While our users certainly brought their own biases to their audit of ORES, they were quick to discover and come to consensus about trends in ORES' issues. Before they had performed this process and shared their results with us, we had no idea that any issues were present. After all, the fitness statistics for the damage detection model looked pretty good—probably good enough to publish a research paper! Their use of thematic analysis seems to be a powerful tool that developers will want to make sure is well supported in any crowd-based auditing support technologies.

How people think about “acceptable” automation. In our case study, Spanish Wikipedians are in the process of coming to agreements about what roles are acceptable for automated agents. Through observation of PatruBOT's behavior, they have decided that the *false discovery rate* (i.e., $1 - \text{precision}$) was too high by watching the bot work in practice and they started their own independent analysis to find quantitative, objective answers about what the real rate is. Eventually they may come to a conclusion about an acceptable *false discovery rate* or they may decide that no revert is acceptable without human intervention.

8 CONCLUSION AND FUTURE WORK

In a world dominated by for-profit social computing and user-generated content platforms – often marketed by their corporate owners as “communities” – [16] Wikipedia is an anomaly. While the non-profit Wikimedia Foundation has only a fraction of the resources as Facebook or Google, the unique principles and practices in the broad Wikipedia/Wikimedia movement are a generative constraint. ORES emerged out of this context, operating at the intersection of a pressing need to deploy efficient machine learning at scale for content moderation, but to do so in ways that enable volunteers to develop and deploy advanced technologies on their own terms than ours. Our approach is in stark contrast from the norm in machine learning research and practice, which involves a more top-down mode of developing the most precise classifiers for a known ground truth, then deploying a complete technology for end-users, who must treat them as black boxes.

The more wiki-inspired approach to machine learning that ORES supports imagines classifiers to be just as provisional and open to skeptical reinterpretation as the content of Wikipedia's encyclopedia articles. And like Wikipedia articles, we suspect some classifiers will be far better than others based on how volunteers develop and curate them, for various definitions of “better” that are already being actively debated. Our case studies briefly indicate how volunteers have collectively engaged in sophisticated discussions about how they ought to use machine learning. ORES's fully open, reproducible, and auditable code and data pipeline – from training data to models to scored predictions – enables a wide and rich range of new collaborative practices. We see ORES as a more socio-technical and specifically CSCW approach to issues around fairness, accountability, and transparency in machine learning, where much attention is placed on technical solutions, like interactive visualizations for model interpretability or mathematical guarantees of different operationalized definitions of fairness. Our approach is specific to the particular genre ecology, work practices, and

cite

values of Wikipedia, and we have shown how ORES has been developed to fit into this complex socio-technical system.

8.1 “Hearing to speech”: lowering barriers to participation

Our goal to design for empowerment lead us in new directions – both from traditional machine learning work more generally and in specific responses to the problems around automation in Wikipedia. Rather than making our own “intervention” based on our own ideas about how to tackle these problems (e.g. [22]), our approach focused on reducing barriers and encouraging a stalled “conversation.” As Bowker and Star discuss when considering participatory design for margins[3], we see our work on ORES as closer to Nell Morten’s concept of “hearing to speech” in contrast to “speaking to be heard” [36]. If we were to build the exact technology or process we think is right for Wikipedia, we would be “speaking to be heard” and forcing our own solution-focused ideas into the conversation about how quality is enacted in Wikipedia. We instead stepped back and asked “What is preventing others from getting involved in this conversation?” then sought to lower those barriers.

ORES does enact our own alternative vision of how quality control should operate in Wikipedia, but only at an indirect meta-level by reflecting a different way of how algorithms should be made available to the populations they govern. Prior ML-based automated tools and bots in Wikipedia often involved a single developer producing both a classifier and an interface or bot that acted on that classifier, coupling these distinct aspects and requiring far more skills and resources if a volunteer wanted to modify or fork an existing tool or bot. There are still many barriers that remain, as creating an ORES classifier remains a complex technical task, and classifiers are not yet as radically open to live editing and discussion as a standard Wikipedia article. However, we have seen firsthand how ORES has supported new kinds of complex conversations and collaborations between volunteer tool developers and Wikimedia Foundation technical staff (or volunteer tool developers and their community of editors).

In taking such a decentralized approach, we run the risk that the conversation (and the processes adaptations) will not go in the directions that we value. Like with Wikipedia’s articles, ORES’s classifiers are used by self-selected individuals who have the means and motivation to participate, and research has repeatedly showed the deep demographic inequalities in participation[? ?]. Yet in this existing situation, we make a conscious choice to design for lowered technical barriers, as well as to foster more legitimate modes of peripheral participation. This more decentralized approach is also a necessity when working within the unique community governance model behind Wikipedia. These generative constraints demanded that ORES would be built as a meta-algorithmic system, encouraging experimentation, discussion, and re-use, as well providing tools for interrogation of the classifiers themselves.

We also note that any system which expands participation brings with it the potential for expanded abuse and harassment, and while we have no firm solutions, we are mindful of such issues and recommend that future work in participatory machine learning. We also do not pretend to be completely value-neutral, as we acknowledge we want to help Wikipedia’s social processes form in ways that align with our values, which include the more complete balance of efficient quality control and newcomer support. We want to see Wikipedia work better, and for us, “better” means that more people who want to contribute will feel welcome to do so and will find their place in Wikipedia. On this goal, this paper provides no direct evaluation of newcomer retention, nor do we look for evidence of improved

newcomer socialization. Instead, we target the early precursors of social change: ecological health and critical reflection.

8.2 Ecological health

In section 6, we show clear evidence of a boom in the ecosystem of quality control technologies. Through the adoption of ORES, new tools have quickly gained relevance. Many of these tools re-mediate the way that quality control happens in Wikipedia. For example, consider Sage Ross's use of ORES' interrogability to support newcomers in developing articles that Wikipedians would find acceptable. By using a quality model to direct newcomers behavior, socialization may be improved at no cost to efficiency—maybe even an improvement from a reviewer's point of view since the system would result in more structurally complete drafts. This addition to the technological conversation around quality control represents a substantial shift from the focus on the post-edit boundary[12] to a focus on pre-review training for newcomers. While Sage's interface has yet to be widely adopted, it represents a key example of a new concept in the technological conversation in Wikipedia.

While ORES has been live for 3 years at the time of writing, the ecological intervention is still young. "ORES" has only recently become commonly known by Wikimedia contributors and we are still building out basic support for the hundreds of different Wikimedia language/project communities. In order to see a fundamental shift in the Wikimedia's technical ecology, we'll likely need to continue observing for 1-2 more years still. But the early signs of ecological health (heavy adoption and increased diversity of quality management technologies) are what we hope to see—long term and continual re-mediation of quality and community management policies, processes, and technologies.

8.3 Critical reflection

In section 7, we show evidence of critical reflection on the current processes and the role of algorithms in quality control. We believe that the case studies that we describe both show that this reflection is taking place and that the wide proliferation of tools that provide surprising alternative uses of ORES suggest that Wikipedians feel a renewed power over their quality control processes. Even if we are wrong about the direction of change that Wikipedia needs for quality control and newcomer socialization, we are inspired by much of the concern that has surfaced for looking into biases in ORES' prediction models (e.g. anons and the Italian "ha") and over what role algorithmis should have in directly reverting human actions (e.g. PatruBOT and DexBot).

Eliciting this type of critical reflection and empowering users to engage in their own choices about the roles of algorithmic systems in their social spaces has typically been more of a focus from the Critical Algorithms Studies literature (e.g. [2, 29]. This literature also emphasizes a need to see algorithmic systems as dynamic and constantly under revision by developers [45]—work that is invisible in most platforms, but foregrounded in ORES. In these case studies, we see that given ORES' open API and Wikipedia's collaborative wiki pages, Wikipedians will audit ORES' predictions and collaborate with each other to build information about trends in ORES' mistakes and how they expected their own processes to function.

8.4 Future work

One of the clear lines of future work that observing ORES in the world drives us toward is improved crowd-based auditing tools. As our case studies suggest, auditing of ORES' predictions and mistakes has become a very popular activity. Even though we did not design

interfaces for discussion and auditing, some Wikipedians have used unintended affordances of wiki pages and MediaWiki’s template system to organize several similar processes for flagging false positives and calling them to our attention. To better facilitate this process, future system builders should implement structured means to refute, support, discuss, and critique the predictions of machine models. With a structured way to report false positives and other real-human judgments, we can make it easy for tools that use ORES to also allow for reporting mistakes. We can also make it easier to query a database of ORES mistakes in order to build the kind of thematic analyses that Italian Wikipedians showed us. By supporting such an activity, we are working to transfer more power from ourselves and to our users. Should one of our models develop a nasty bias, our users will be more empowered to coordinate with each other, show that the bias exists and where it causes problems, and either get the model’s predictions turned off or even shut down ORES.

We also look forward to what future work in the space of critical algorithm studies will do with ORES. As of writing, most of the studies and critiques of *subjective algorithms*[51] focus on large for-profit organizations like Google and Facebook—organizations that can’t afford to open up their proprietary algorithms due to competition. Wikipedia is one of the largest and most important information resources in the world. The algorithms that ORES makes available are part of the decision process that leads to some people’s contributions staying and others being removed. This is a context where *algorithms matter to humanity*, and we are openly experimenting with the kind of transparent and open processes that *fairness and transparency in machine learning* researchers are advocating. Yet we have new problems and new opportunities. There is a large body of work exploring how biases manifest and how unfairness can play out in algorithmically mediated social contexts. ORES would be an excellent place to expand the literature within a real and important field site.

Finally, we also see potential in allowing Wikipedians, the denizens of Wikipedia, to freely train, test, and use their own prediction models without our engineering team involved in the process. Currently, ORES is only suited to deploy models that are trained and tested by someone with a strong modeling and programming background. That doesn’t need to be the case. We have been experimenting with demonstrating ORES model building processes using Jupyter Notebooks^{41,42} and have found that beginning programmers can understand the work involved. This is still not the holy grail of crowd developed machine prediction—where all of the incidental complexities involved in programming are removed from the process of model development and evaluation. Future work exploring strategies for allowing end-users to build models that are deployed by ORES would surface the relevant HCI issues involved and the changes the technological conversations that such a margin-opening intervention might provide.

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⁴¹<http://jupyter.org>

⁴²e.g. https://github.com/wiki-ai/editquality/blob/master/ipython/reverted_detection_demo.ipynb

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A APPENDIX

A.1 ORES system details

In this section, we describe some of the details of the ORES system.

A.1.1 Score documents. The predictions made by through ORES are human- and machine-readable. In general, our classifiers will report a specific prediction along with a set of probability (likelihood) for each class. By providing detailed information about a prediction, we allow users to re-purpose the prediction for their on use. Consider article quality (wp10) prediction output in Figure 9.

```
"wp10": {
  "score": {
    "prediction": "Start",
    "probability": {
      "FA": 0.0032931301528326693, "GA": 0.005852955431273448,
      "B": 0.060623380484537165, "C": 0.01991363271632328,
      "Start": 0.7543301344435299, "Stub": 0.15598676677150375
    }
  }
}
```

Fig. 8. Result of <https://ores.wikimedia.org/v3/scores/enwiki/34234210/wp10>

A developer making use of a prediction like this may choose to present the raw prediction “Start” (one of the lower quality classes) to users or to implement some visualization of the probability distribution across predicted classes (75% Start, 16% Stub, etc.). They might even choose to build an aggregate metric that weights the quality classes by their prediction weight (e.g. Ross’s student support interface[42] or the *weighted sum* metric from [20]).

A.1.2 Model information. In order to use a model effectively in practice, a user needs to know what to expect from model performance. E.g. how often is it that when an edit is predicted to be “damaging” it actually is? (*precision*) or what proportion of damaging edits should I expect will be caught by the model? (*recall*) The target metric of an operational concern depends strongly on the intended use of the model. Given that our goal with ORES is to allow people to experiment with the use and reflection of prediction models in novel ways, we sought to build an general model information strategy.

```

"damaging": {
  "type": "GradientBoosting",
  "version": "0.4.0",
  "environment": {"machine": "x86_64", ...},
  "params": {"center": true, "init": null, "label_weights": {"true": 10},
    "labels": [true, false], "learning_rate": 0.01, "min_samples_leaf": 1,
    ...},
  "statistics": {
    "counts": {"labels": {"false": 18702, "true": 743},
      "n": 19445,
      "predictions": {"false": {"false": 17989, "true": 713},
        "true": {"false": 331, "true": 412}}},
    "precision": {"labels": {"false": 0.984, "true": 0.34},
      "macro": 0.662, "micro": 0.962},
    "recall": {"labels": {"false": 0.962, "true": 0.555},
      "macro": 0.758, "micro": 0.948},
    "pr_auc": {"labels": {"false": 0.997, "true": 0.445},
      "macro": 0.721, "micro": 0.978},
    "roc_auc": {"labels": {"false": 0.923, "true": 0.923},
      "macro": 0.923, "micro": 0.923},
    ...
  }
}

```

Fig. 9. Result of <https://ores.wikimedia.org/v3/scores/enwiki/?model.info&models=damaging>

The output captured in Figure 9 shows a heavily trimmed JSON (human- and machine-readable) output of *model.info* for the “damaging” model in English Wikipedia. Note that many fields have been trimmed in the interest of space with an ellipsis (“...”). What remains gives a taste of what information is available. Specifically, there is structured data about what kind of model is being used, how it is parameterized, the computing environment used for training, the size of the train/test set, the basic set of fitness metrics, and a version number so that secondary caches know when to invalidate old scores. A developer using an ORES model in their tools can use these fitness metrics to make decisions about whether or not a model is appropriate and to report to users what fitness they might expect at a given confidence threshold.

A.1.3 Explicit pipelines. We have designed the process of training and deploying ORES prediction models is to be repeatable and reviewable. Consider the following code that represents a common pattern from our model-building Makefiles:

Essentially, this code helps someone determine where the labeled data comes from (manually labeled via the Wiki Labels system). It makes it clear how features are extracted (using the `revscoring extract` utility and the `feature_lists.enwiki.damaging` feature set). Finally, this dataset of extracted features is used to cross-validate and train a model predicting the “damaging” label and a serialized version of that model is written to a file. A user could clone this repository, install the set of requirements, and run `make enwiki_models` and expect that all of the data-pipeline would be reproduced, and an exactly equivalent model obtained.

```

datasets/enwiki.human_labeled_revisions.20k_2015.json:
    ./utility fetch_labels \
        https://labels.wmflabs.org/campaigns/enwiki/4/ > $@

datasets/enwiki.labeled_revisions.w_cache.20k_2015.json: \
    datasets/enwiki.labeled_revisions.20k_2015.json
cat $< | \
revscoring extract \
    editquality.feature_lists.enwiki.damaging \
    --host https://en.wikipedia.org \
    --extractor $(max_extractors) \
    --verbose > $@

models/enwiki.damaging.gradient_boosting.model: \
    datasets/enwiki.labeled_revisions.w_cache.20k_2015.json
cat $^ | \
revscoring cv_train \
    revscoring.scoring.models.GradientBoosting \
    editquality.feature_lists.enwiki.damaging \
    damaging \
    --version=$(damaging_major_minor).0 \
    (... model parameters ...)
    --center --scale > $@

```

Fig. 10. Makefile rules for the English damage detection model from <https://github.com/wiki-ai/editquality>

By explicitly using public resources and releasing our utilities and Makefile source code under an open license (MIT), we have essentially implemented a turn-key process for replicating our model building and evaluation pipeline. A developer can review this pipeline for issues knowing that they are not missing a step of the process because all steps are captured in the Makefile. They can also build on the process (e.g. add new features) incrementally and restart the pipeline. In our own experience, this explicit pipeline is extremely useful for identifying the origin of our own model building bugs and for making incremental improvements to ORES' models.

At the very base of our Makefile, a user can run `make models` to rebuild all of the models of a certain type. We regularly perform this process ourselves to ensure that the Makefile is an accurate representation of the data flow pipeline. Performing complete rebuild is essential when a breaking change is made to one of our libraries. The resulting serialized models are saved to the source code repository so that a developer can review the history of any specific model and even experiment with generating scores using old model versions.

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