Provocation: Contestability in Large-Scale Interactive NLP Systems

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1 Overview
Designing computational systems for language analysis means, increasingly, designing for interactions with natural language processing (NLP) algorithms. For example, sentiment analysis, topic modeling, toxicity classification, and other language modeling techniques have become common in interactive user-facing systems. These developments raise novel, complex challenges, both in terms of designing such systems and user’s interactions with them (Baumer et al., 2020). Accordingly researchers have advocated for rethinking interactive ML systems that involve users at every stage of the system (Amershi et al., 2014). For example, Horvitz’ principles for effective “mixed-initiative” systems include querying users about goals and preferences and scouting system precision to match users’ needs (Horvitz, 1999). Other approaches include value-centered design (Knobel and Bowker, 2011), transparency in design (Ananny and Crawford, 2018) and more recently contestability (Hirsch et al., 2017). Despite these various proposed approaches for ML-based systems, situating the discussion in the context of interactive NLP systems, in particular, has remained elusive. Each of these design principles (mixed-initiative, value-centered, transparency, contestability) can claim it’s own spot for a full-day workshop discussion. Hence, to scope the conversation for this workshop, we will primarily focus on contestability in NLP systems in this provocation piece.

Contestability: The notion of contestability originates from the need for contesting or challenging machine predictions (Hirsch et al., 2017; Kluttz et al., 2018). For example, contestability in recidivism prediction systems or health behavior prediction systems. Here we argue the need for exploring contestability in large-scale online systems and in particular NLP systems. With respect to language-based systems, consider the Perspective API developed by Google’s Counter-Abuse Technology team to identify toxic language in text. The technology has now been integrated within the New York Times comment interface to facilitate large-scale moderation of potentially toxic and obscene comments on news stories. However, the same technology has also incorrectly discovered a positive correlation between identity terms containing information on race or sexual orientation (e.g., the phrase “I am a gay black woman” received a high toxicity score) (developers.google.com). But we do not yet have an established way to contest these decisions made by NLP algorithms integrated within large socio-technical systems (in this case a news platforms with widespread readership).

Perhaps the closest form of contestability research in large-scale online systems relates to efforts around auditing algorithmic systems for bias (Bozdag, 2013; Chen et al., 2018), discrimination (Chen et al., 2016; Hannak et al., 2014; Mikians et al., 2012), and fairness (Dwork et al., 2012). While audit studies is a way to detect undesirable behavior in large-scale “black-boxed” Web systems, allowing users to meaningfully contest such undesirable behavior will offer ways to help people not only make sense of an algorithm’s behavior, but also restore human agency in systems that are intertwining humans and non-human agents (Ananny and Crawford, 2018). How can we design for contestability in large-scale online NLP systems? What are the goals when designing for contestability in online systems? What are the challenges and limitations of the contestability ideal?

2 Designing Contestability in Large Online NLP Systems
The first step in designing for contestability is to layout the goals we would like to achieve when...
bringing the ideal of contestability in large-scale online socio-technical systems driven by language technologies. In most predictive systems, the goal is to contest a machine prediction in an attempt to correct a wrong decision. For example, in healthcare systems, contestability strives to improve the accuracy of ML models by deploying the system among expert users and then soliciting feedback from them (Hirsch et al., 2017). However, the goal in large online social systems is more nuanced. For example, in an online ride sharing system a driver might want to contest their ride and route recommendation, a rider might want to contest the tip suggestion or the matched driver, resulting in a multi-stakeholder contestability problem. In this particular case, it is a complex assemblage of the algorithm and the two stakeholders (the driver and the rider) who are both using the same instance of the ride sharing platform.

Here I outline two examples of NLP-based online systems along with the phenomenon that could be contested and the contestation goal.

**Contestability in Moderation Systems.** Content moderation is a predominant practice in almost all social media platforms, be it, Twitter, Facebook, Reddit, and is now increasingly common in news platforms (e.g. Perspective APIs usage in NYT comment moderation interface). Most content moderation systems are based on linguistic models (see (Gunasekara and Nejadgholi, 2018) for a review). However, none currently have designs in place where a user can appeal against content removal. If the goal is to contest moderation practices, how do we design to meet that goal? Some social media platforms, like Reddit, have a two-tier governance structure, the first tier enforced by the platform’s content policy and a 2nd tier rule enforcement set by the human moderators within the community. Such differences in governance structures across online platforms make it almost impossible to come up with a “one size fits all” contestation goal when building a language-based moderation system.

**Contestability in Information Retrieval Systems.** Language models are fundamental to driving online information retrieval systems, such as search and recommendation systems (see (Zhai, 2008; Hiemstra, 2001; Liu and Croft, 2004)). For a regular user, online search and recommender systems have become an integral part of their daily lives. Despite their increasingly important role in selecting, presenting, ranking, and recommending what information is considered most relevant for us—a key aspect governing our ability to meaningfully participate in public life (Gillespie, 2014), there is no notion of whether this information is credible or whether the returned results are reinforcing existing societal biases. Neither do users have any means to contest or challenge to understand why they are seeing what they are seeing on search platforms and their recommendation feeds. The lack of contestability in search platform coupled with an unwavering trust placed in search engines can together lead to misinformed citizenry. Our goal for including contestability in search systems, would be to contest potential inaccurate results, unreasonable rankings (e.g., a low credible alternative news source ranked higher than a reputed journalistic source), inaccurate recommendations (for e.g., YouTube recommending more pro-conspiracy videos after user watches one anti-vaccine video) or biased results.

2.1 Why, When, and How to Contest

What are the ways in which we can design for contestability in online systems? Does contestability help users improve their understanding and trust of large-scale online systems? One possibility is to draw inspiration from the design of intelligibility in context-aware systems (Lim et al., 2009). Of particular interest are end-user programming systems which allowed users to ask questions when their expectations were not met (Ko and Myers, 2004). Users asked why did questions when something unexpected happened and why not questions when something expected did not occur (Ko and Myers, 2004, 2009). Another line of work that is relevant is (Kulesza et al., 2011, 2009) What You See is What You Test for Machine Learning (WYSIWYT/ML) method for systematic testing of machine learning applications. WYSIWYT/ML offers three key functionalities: 1) advises the user about which predictions to test, 2) contributes more tests “like” the user’s, 3) measures how much of the assistant’s reasoning has been tested, and 4) continually monitors over time whether previous testing still “covers” new behaviors learned. Inspired from these approaches, here I lay a list of intuitive questions that can inform the design of contestability. By no means, this list is exhaustive. The hope is that discussions at the workshop will
refine and expand the list.

1. **Why**: Why did the online system do X, where X can be recommend, suggest, rank, moderate, etc.?

2. **Why Not**: Why did the system not do Y? For example, in designing contestability for content moderation in social platforms, a user can contest why did the system did not remove this other post?

3. **What if**: What would the system do if Z happens? For example, what would Amazon recommend if I bought the lower ranked product from its ranked product list?

4. **How to**: How can I get the system to do A, given the current context? For example, how can I get this ride sharing service to pair me with a female driver, given that I am a woman and I am traveling in a region notorious for crimes against woman?

### 3 Challenges for Contestability in Large Online NLP Systems

Infusing contestability in complex online systems can lead to unforeseen challenges. The ideal of contestability as a means to provide agency to users can be limited in multiple ways. Here I list a few.

**Contestability can unintentionally occlude.** Ananny and Crawford (Ananny and Crawford, 2018) in their critical interrogation of the ideal of transparency argue that transparency to promote understandability of black-box ML systems can backfire in various ways, one of them being intentional occlusion—"visibility produces such great quantities of information that important pieces of information become inadvertently hidden in the detritus of the information made visible.” Contestability can also result in similar occlusion. For example, an online system that offers too many options for contesting the system’s decision may unnecessarily distract the user from the central information that the system intends to offer.

**Contestability can reinforce pre-existing biases.** Considering that most algorithms driving large-scale online systems are personalized—i.e., they serve results based on user’s past behavior—such personalization tend to re-enforce pre-existing biases. Imagine a factuality model that sits within an online system and determines the credibility of content based on linguistic features (such models already exist in the literature; see (Soni et al., 2014) and (Mitra et al., 2017). Offering real-time corrections every time the user contests search results that goes against their pre-existing beliefs, often act as mandates and can backfire by inadvertently provoking users into attitude consistent misperceptions (Garrett and Weeks, 2013). Another unforeseen scenario can occur for certain classes of search queries, popularly known as “data voids”—search terms for which the available relevant data is limited or non-existent (Golebiewski and boyd, 2018). Allowing the user to contest and introduce problematic corrections into the system defeats the purpose of contestability in such scenarios.

**Contestability has temporal limitations: When to introduce contestability?** Decisions about when to allow contestability in an online social system can get too complex too quickly to reach any useful design decision. A large-scale social system has multiple stakeholders, each of whose contestability action at any point in time can effect the system and in turn the contestability decision of the next action. For example, a language model working in the moderation interface of a news website has to balance between several stakeholders: the users commenting on the news story, the moderator managing the commenting system, the reporter who wrote the story, and the editor who reviewed the story. Moreover online systems are continually changing over time as data are being generated, interacted, and added by users, and as the number of users interacting with the system change. Thus when thinking about designing for contestability in multi-stakeholder online systems, the notion of temporal dimension is key.

I hope that the workshop will provide opportunities to brainstorm on these complex questions and stir new questions in the domain.

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