You Don’t Know Search: Helping Users Find Code by Automatically Evaluating Alternative Queries

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***Abstract*—Tens of thousands of engineers use Sourcegraph day-to-day to search for code and rely on it to make progress on software development tasks. We face a key challenge in designing a query language that accommodates the needs of a broad spectrum of users. Our experience shows that users express different and often contradictory preferences for how queries *should* be interpreted. These preferences stem from users with differing usage contexts, technical experience, and implicit expectations from using prior tools. At the same time, designing a code search query language poses unique challenges because it intersects traditional search engines and full-fledged programming languages. For example, code search queries adopt certain syntactic conventions in the interest of simplicity and terseness but invariably risk encoding implicit semantics that are ambiguous at face-value (a single space in a query could mean three or more semantically different things depending on surrounding terms). Users often need to disambiguate intent with additional syntax so that a query expresses what they actually want to search. This need to disambiguate is one of the primary frustrations we’ve seen users experience with writing search queries in the last three years. We share our observations that lead us to a fresh perspective where code search behavior can straddle seemingly ambiguous queries. We develop Automated Query Evaluation (AQE), a new technique that automatically generates and adaptively runs alternative query interpretations in frustration-prone conditions. We evaluate AQE with an A/B test across more than 10,000 unique users on our publicly-available code search instance. Our main result shows that relative to the control group, users are on average 22% more likely to click on a search result at all on any given day when AQE is active. We share our technique, learnings, and implementation that made it possible for a substantial number of users to now see and click on results that they would not have seen otherwise.**

I. INTRODUCTION

Sourcegraph[1] is a code search engine used by over 1 million engineers, and used at companies like Dropbox, Cloudflare, Uber, Reddit, and many more. A free, open-source instance of Sourcegraph also powers code search for millions of open source repositories.[2] Developers use Sourcegraph to reference existing implementations, navigate code, or find usage examples, in line with previous studies on how developers use code search [1]. Every user starts a code search by typing a query into Sourcegraph’s search bar. This single search bar encodes all the expressive power for filtering repositories or files, searching with regular expressions, or applying boolean operators (`AND`, `OR`) to search terms. A user’s familiarity with the query language influences whether they can write a query that returns meaningful results. Previous studies show developers frequently reformulate queries and run successive searches in a short time span to home in on a desired result [1]. At the same time, we’ve seen a broad spectrum of users search code with Sourcegraph. First-time users may be unfamiliar with query filters, or even general pattern matching with regular expressions. Even familiar users will tweak queries to get results. User interaction with a query string across varying degrees of proficiency underscores a single important design principle: help users find useful results quickly by (a) surfacing the expressive capabilities of the language, and (b) reducing the burden to modify or reformulate queries. Beyond learning search syntax, Sourcegraph users regularly express frustration via our feedback channels that queries aren’t *interpreted* the way they expect.

In the past three years we’ve seen users express the gamut of differing personal preferences for how Sourcegraph *should* interpret certain queries. At the surface level, designing a consistent and predictable language for searching code seems deceptively simple. Our experience reveals that query design presents one of the most contentious and difficult challenges for a code search solution—not because it is difficult to design a query language with consistent syntax and semantics, but because users regularly express contradictory preferences on how queries should be interpreted.

To quote or not to quote? An example to illustrate complexity in interpreting code search queries. We often see Sourcegraph users get tripped up by whether quotes in the search string are treated literally or not. Consider two users who search for a quoted string like `"v1.3"`. User #1 quotes `v1.3` because they want to search for that exact string (perhaps leaning on their experience using Google search). User #2 enters a quoted string because they want to find that string *including* quotes (it helps them narrow down results to a JSON configuration file like `"version": "v1.3"`). Either interpretation is reasonable, and users will expect or prefer certain behavior depending on e.g., previous experiences, tools, or the task at hand when running the search. Nevertheless both these users exist, and they are on opposite sides of the “interpretation camp”. Unfortunately, from a language design perspective, there is no objectively better way to interpret the presence of quotes in this scenario—either may be preferred over the other. In practice, attempting to resolve this issue by allowing users to configure individual preferences

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[1] about.sourcegraph.com

[2] sourcegraph.com/search

for query behavior is highly problematic in a collaborative context. For example, users could share syntactically identical queries with others, who then see different or “wrong” results based on their configuration (we elaborate on this complexity in Section §II). Thus the tool builder faces a crucial challenge: ambiguity must be resolved so the language is consistent (we decide either quotes are literal or not), and immediately once resolved, the language now grants a particular convenience to one type of user, while inconveniencing the other. For example, supposing we decide quotes are *not* treated literally, User #1 perceives no friction, but User #2 sees unwanted results (maybe a comment containing the string `v1.3`). User #2 now has to reformulate their query to escape the quotes (e.g., `\"v1.3\"` or `"\"v1.3\""`). Going the other way, where quotes *are* significant, User #2 perceives no friction, but User #1 sees results including quotes, or worse, they may not see *any* results because there are no matches that include quotes (and they end up missing results for the `v1.3` pattern they were looking for). This time User #1 will have to modify their query.

Despite this complexity, a best-in-class code search tool must rise to the challenge to accommodate all potential users: It must find ways to reconcile contradictory expectations, educate users about capabilities, and reduce query modification and friction. This is an acute challenge we’ve faced and a demanding technical task facing every code search tool today. Recently we’ve approached this problem with fresh insight, prompting a new solution to *automatically generate and run alternative interpretations*. The rest of this paper proceeds with the following outline and contributions:

> **Principles for code search design re: interpreting queries.** Section II shares background principles and scope behind building a code search engine (query syntax, expressive power, result ordering) that bear specifically on query interpretation.
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> **Practical challenges in query interpretation.** Section III details our domain-specific challenges when developing query languages for an industrial-strength code search tool. We’ve condensed hundreds of pieces of user feedback to identify ambiguity in user expectations and how these relate to a consistent query syntax and semantics. We believe our findings are general and tool-agnostic, with relevance to design choices behavior found in all the major existing code search tools (e.g., [2], [3], [4]) and those that will appear in future.
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> **A new approach for Automated Query Evaluation (AQE).** Section IV presents our automated query evaluation framework to alleviate major issues in language ambiguity and help users find useful results more easily. Our solution uniquely goes beyond existing code search recommendation approaches by incorporating both static properties (query transformations) and dynamic runtime behavior (inspecting whether generated queries find results, which are then automatically displayed to the user).
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> **Empirical results that demonstrate the effectiveness of our approach.** In Section V we evaluate AQE with an A/B test across 10,000 unique users over 25 weekdays on our publicly-available code search instance, Sourcegraph.com. We investigate click rate as a positive indicator that users gain utility from code search and allows them to make progress on their task at hand. Our main result shows that when AQE is active, users are **22%** more likely to click on result at all on any given day, compared to the control group.

We discuss related work in Section VI and conclude in Section VII.

II. BUILDING A CODE SEARCH ENGINE FOR ALL: QUERY DESIGN PRELIMINARIES FROM THE TRENCHES

Sourcegraph aims to provide code search to the broadest spectrum of users, from beginner programmers who have never written regular expressions, to power users who can craft extremely sophisticated queries (e.g., search for a regular expression in `package.json` files only in repositories that have been committed to in the last month). At present, Sourcegraph interprets queries precisely with respect to a simple language grammar. Broadly, a search query contains space-separated *patterns* (like `func parse`) and *filters* (like `path:package.json`). Filters specify a field prefix, like `path:`, followed by a value like `package.json` to specify that only file paths matching `package.json` should be searched. Boolean operators like `AND`, `OR`, `NOT` apply to patterns and filters to build expressions. This choice of syntax is largely consistent and conventional among major code search tools, similarly found in Google Code Search, GitHub Code Search, and OpenGrok. Although opportunities exist to design engines that interpret queries more freely (e.g., as prompts to a machine-learned model), the state of code search today has established the value of consistent and well-defined query languages to precisely find results and craft queries with extensive and predictable expressive power.[3] We therefore scope our discussion to enabling greater ease of use when designing such a well-defined language when talking about query interpretation. Within this scope, we share our perspective on technical factors influencing code search usage with respect to query design.

What is special about query syntax for code search? Designing a code search language presents unique domain challenges in the intersection of traditional search engines and full-fledged programming languages. We draw on our experience and a cursory survey of related code search tools [2], [3], [4] to reveal common characteristics in this overlap. Table I distills these characteristics. In general **Properties** add constraints to language design, which can lead to greater burden and potential friction when users interact directly with a query syntax. Consequently all major industrial code search engines today are influenced by, and account for, query **Design Implications** in some shape or form. While not meant to be exhaustive, these properties represent the most challenging aspects of language design in our experience, because they

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[3] Albeit sometimes unforgiving to newcomers.

TABLE I: Query syntax properties in major code search engines today, and implications for language design and usability.

Property	Design Implication
single search string	strive for terse expressive power and readability (e.g., choice of attributing semantic meaning to spaces in different contexts)
support searching punctuation	requires escaping or disambiguation (patterns conflict with reserved syntax in query language)
support sublanguages (e.g., regular expressions)	requires escaping or disambiguation (dialect syntax conflicts with literal interpretation or query language)
enable collaborative sharing	choice of consistent query syntax and semantics (it is exceedingly complex to support individual preferences for interpreting syntax or disambiguating; avoided by code search engines today)

constrain design that must be somehow reconciled with user desires and expectation. They lie at the root of long internal discussions on how code search ought to work, and give rise to much user confusion and misunderstandings ("Why do I see these results? Why don't I see *any* results? How do I set my preference to interpret patterns as regular expressions by default?"). We elaborate on these properties below.

Singular search query strings and punctuation. Like Google search or other traditional search engines, code search UIs generally offer a single input field (or maybe a small set of input in the case of OpenGrok). In contrast, searching literally over code instead of web content means that users are much more likely to search for literal punctuation like quotes (as in our leading example), or other syntax that correspond to code constructs: `i < j`, `parse(`, `struct {`, `!flag`. This is significant because searching for punctuation increases the likelihood that search terms conflict with reserved syntax in the query language (e.g., parentheses for grouping search expressions like `(foo OR bar)`). Further, and unlike plain text search, major code search engines [2], [3], [4]) effectively embed support for sublanguages like regular expression syntax. Supporting such dialects also heighten the potential for syntax conflicts with search terms, or the query language itself.

Semantically and contextually significant spaces. Code search queries strive to be terse and less complicated than full-fledged programming or database languages, but share overlap in expressive power (boolean operations, conditional clauses). Most queries fit on a single line, and whether by consequence or design, a majority of today's code search engines apply some semantic meaning to spaces in the interest of convenience and readability. The semantic meaning of spaces is a design choice, and may differ across engines and between query terms. Some choices include spaces to mean any of: (1) search for multiple terms anywhere in a document (without respect to ordering); (2) search for terms *with* respect to ordering (e.g., on the same line); or (3) just lexically separate search filters. Ultimately, shorthand conventions allow users to write more terse queries like `repo:ase path:.tex table` instead of `repo:ase AND path:.tex AND table`. Such decisions can generally enhance usability, but may sacrifice the precise intent of a user in other contexts and introduce ambiguity (we elaborate in Section III).

Users want it their way, but that leads to bigger problems. The terse nature of search queries tend to invite ambiguity, and we've seen users prefer different defaults for how queries should be interpreted. Drawing on our previous example, users may prefer that quotes are interpreted literally, while others may not. Instinct suggests that the search tool could provide a way for users to configure personal defaults. In other words, the tool grants users some agency over the query semantics. In practice we find this idea does not work. Code search engines today are useful in collaborative settings, where developers or coworkers share links to search results, and queries are the source of input and truth. If the interpretation of that input diverges across users, we violate a fundamental tenet: consistent, predictable results. URLs or other serializable formats could in theory encode values that indicate the intended (perhaps custom) semantics of a particular query to overcome this challenge. In practice, no code search engine to our knowledge has been able to identify a user-friendly way to ensure users copy a URL or share a query format that encodes how query semantics. It is simply too easy and natural for users to copy a query string in the search input box and share it as-is. In this light, it is exceedingly difficult to cater to individual preferences for query interpretation. Thus, in identifying mechanisms to reconcile ambiguity, customizing query interpretation is not practical for us. Syntax needs to be interpreted consistently to avoid further confusion, and reconciling potential ambiguity requires a different approach.

III. CHALLENGES IN AMBIGUITY: OBSERVING THE PITFALLS THAT USERS EXPERIENCE

This section lays out practical examples and "fork in the road" decisions that have accompanied the design of our industrial-strength code search query language at Sourcegraph. We regularly receive user feedback from our customer support channels and in-app feedback box. In the last three years we've received hundreds of pieces of user feedback on experiences, opinions, and frustrations specifically dealing with query syntax and semantics. We condense this feedback qualitatively in Table II, presenting the most common query **Pitfalls** users experienced. Every pitfall leads to **Ambiguity** with more than one plausible interpretation, and we give representative scenarios where a design choice in our tool behaves contrary to a user expectation or desire. The difference in our design choice (**Us** in the table) versus expected behavior (by the **User**) is *interchangeable*. In fact, Sourcegraph currently supports two distinct modes for interpreting queries, due to some of the

TABLE II: A qualitative summary of how users experience pitfalls due to ambiguity in search query intent. The ambiguous columns are *interchangeable*, and we've seen users express a preference for either interpretation. As a matter of consistent language design, a tool can typically implement only one sensible default, and sacrifices syntactic convenience for expressing alternatives..

		Ambiguity	
Query	**Pitfall**	**Us: We guess you want to...**	**User: I actually want to...**
`func parse`	Is term order significant?	find matches of `func AND parse` anywhere in a file → ordering *doesn't* matter	find the string `func␣parse` on a single line → ordering matters; the pattern corresponds to a specific function definition
`"v1.3"`	Are quotes meaningful?	find `v1.3` *without* quotes	find `"v1.3"` *with* quotes inside config files
`swing.*`	Interpret as regular expression dialect?	match `swing` followed by anything → interpret `.*` as a wildcard regular expression.	find wildcard imports in Java files → interpret `.*` literally, *not* as a regular expression.
`func.*(`	Interpret as regular expression dialect?	try search for an regular expression, but it's *invalid* → Tell user `(` might need to be escaped. Or did the user intend to search literally?	search a valid regular expression `func.*\(` → User didn't realize need to escape `(`
`should not fail`	Interpret `not` as a boolean operator or as a literal search term?	find matches in files for `should`, but exclude them if they contain `fail`	find error messages and search literally for `should not fail`

contentious issues in ambiguity shown here.[4] We elaborate on the concrete examples below.

The foremost behavioral pitfall in Sourcegraph is whether a sequence of patterns like `func foo(bar, baz` means "search for each space-separated term anywhere in a file" (ordering does not matter) or whether the whitespace should be interpreted literally on a single line (ordering matters). The same user may even prefer one behavior over the other in different contexts, e.g., searching in a more fuzzy way, versus pinpointing exact code. Language features exist to enable both possibilities, but users may need to manually reformulate queries to achieve what they want. For example, patterns can be explicitly separated by `AND` to express that ordering does not matter, or alternately, users can rely on the default behavior that concatenates patterns, or users can quote patterns in a filter `content:"func foo(bar, baz)"` for absolute clarity and with additional effort.

As in the leading example, users may start using Sourcegraph with a preconceived idea of whether quotes are significant or not. Many have found it useful to search quotes literally (cf. Table I, supporting search for punctuation) while others rely on quotes to express exact intent or to disambiguate a regular expression. Because we want to maintain consistent behavior (cf. Table I, collaborative sharing), this is not a preference we can accommodate in an individual user setting. Instead, users may experience friction until they become familiar with the default behavior, and mechanisms to change the behavior (e.g., UI toggles or additional syntax to disambiguate intent).

Sourcegraph currently supports the RE2 regular expression dialect.[5] Supporting this sublanguage (cf. Table I) leads to user confusion both on (a) whether RE2 metasyntax is interpreted by default and (b) the realization that a regular expression syntax may be invalid (and inconveniently so!). It is generally difficult to infer whether a user intends their pattern to be interpreted as a regular expression. We might speculate that patterns containing syntax like `\w+` or `.*?` is indicative, but in practice the opportunities for ambiguity and conflict are too high to *override* the default behavior heuristically.

A final balancing act involves adding more expressive power and syntax to the query language. In most code search engines (Sourcegraph being no exception) query strings are singular inputs (cf. Table I single search string). This grants some usability convenience, limiting the need for interactive inputs like moving the cursor to multiple input fields or excessive quoting in a command line. The decision carries the tradeoff that every addition to the language, such as keywords or punctuation, increase the likelihood of ambiguity with what a user may intend to search for literally. In practice, visual cues alleviate ambiguity for cases like these (e.g., Sourcegraph highlights keywords like `NOT`). Unfortunately this still requires users to reformulate their query when keywords or punctuation conflict with the desired meaning.

IV. Mechanizing Auto Query Evaluation to Straddle Ambiguity

Sections II and III cover the challenges we've faced to reconcile user expectation and tool design. We realized that

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[4] Roughly, one mode supports regular expression syntax as a first-class interpretation, and the other prefers literal syntax. UI toggles allow switching between modes.

[5] github.com/google/re2/wiki/Syntax

`context:global` `jest test typescript`

Smart Search is showing **related results** as your query found **no results**. Don't want these? Disable **Smart Search**

To get additional results, Smart Search also ran these queries:

- Apply language filter for pattern (1 result) → `lang:TypeScript jest test`
- Apply language filter for pattern, AND patterns together (500+ results) → `lang:TypeScript (jest AND test)`

Fig. 1: Search query input with a dialog box below. The `Smart Search` dialog box illustrates our search feature that implements AQE. This dialog box displays when a query like `jest test typescript` does not return results *and* we identify that it's possible to interpret the query in different ways based on our rules. The first rule detects that we can interpret `typescript` as a language. We display the corresponding action to `Apply language filter for pattern` and the resulting query, which prepends a `lang` filter to form `lang:TypeScript`. Note that unlike traditional static query suggestions, our engine *dynamically evaluates* alternative queries and *only* reports the action taken if at least some results exist for an alternative. For example, we report the number of results (e.g., `1 result` associated with the first alternative, and `500+ results` for the second) in prioritized order. The results of these queries are also shown immediately below the dialog box (omitted in the figure for brevity) giving users a list of results without requiring them to click on suggestions.

we cannot establish a set of default query behaviors that suit all users. At best, we might converge on useful defaults for most users, and a substantial number of remaining users will invariably experience some friction until they identify the ways to disambiguate intent in our language (or, at worst, abandon the tooling). These observations motivate us to consider a fresh perspective so that tool behavior could straddle ambiguity and better accommodate user expectations. We developed Automated Query Evaluation (AQE) which automatically runs queries under alternative interpretations. This approach differs substantially from current *"Did you mean..."* suggestions found in typical code search tools today. Standard practice in code search tools today implement checks that predominantly rely purely on a query's *syntactic* properties (e.g., check whether the pattern contains quotes, or whether it matches a value like `Python`, which might mean the user only wants to search over Python files). However, because users often have varying expectations of query *semantics* (Section III), static checks can only partially alleviate user confusion or friction. Automated Query Evaluation fills this gap by first requiring that alternative, suggested queries actually produce one or more results before displaying this alternative to the user. It then goes a step further by also *showing those results immediately* (up to some threshold of results) without requiring the user to click on the suggestion or reformulate the query.

In contrast, simple query suggestions typically do not guarantee whether a suggestion returns results over a data set (and so, if a user accepts the suggestion it may return no results and not help them at all). Even then, users must respond to suggestions manually (click on a suggestion or reformulate the query). With AQE, we develop a framework to write rules that transform the user's original query *and evaluates alternatives at runtime* to ensure that suggested queries produce additional results that the user may find useful. The approach seems straightforward and promising, but it is deceptively difficult to implement well in an industrial-strength tool that affects the day-to-day workflow of tens of thousands of developers. We next discuss our goals behind AQE and its implementation challenges.

One overarching goal is to ensure **minimal disruption to existing behavior** while developing AQE. Users are sensitive to stark changes in tools they use frequently, and our primary interest is to overcome disappointing user experiences in the "gray area" of what a search query means while staying true to any existing, learned expectations. We identified that the area of greatest opportunity exists where user queries syntactically conform to a known **Pitfall** (cf. Table II) *and* when a user sees **no results** for their original query. We can identify queries that experience potential pitfalls *statically*, but we must rely on *runtime behavior* to determine whether an alternative query may yield results. Our implementation thus transforms the user's original query to try alternative interpretations, but stipulates that the result of evaluating those queries must return results before displaying a viable alternative and its outcome. Fig. 1 shows the user-facing component that implements AQE.

A. *Building a lazy query generator*

A subsequent goal of AQE is to accommodate a **configurable suite of potential transformation rules** that can overcome query pitfalls. We identified a recurring set of issues based on user feedback (Table II) and seek a way to encode multiple rules and to test their effectiveness. We've mechanized AQE with a set of atomic rules summarized in Table III that correspond to the most problematic pitfalls. Rules are implemented in Sourcegraph as query passes using a visitor framework, written in Go. It is natural for multiple atomic rules to apply independently to a user's original query, and it is also natural for atomic rules to compose. The second suggestion in Fig. 1 illustrates an instance of composite rules: apply a `language filter` to `typescript` and then also convert the

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[6] Roughly, we detect whether two or more metasyntax operators exist. The full implementation is available online.

TABLE III: The main query transformation rules we evaluated with AQE. These mechanize the alternative interpretations associated with common pitfalls and frustrations we identified in user feedback (Table II).

Rule name	**Example application**	**Description**
`and`	`func␣parse` → `func AND parse`	converts ordered, space-separated patterns to an expression that searches for files containing all of those patterns in any order
`unquote`	`"v1.3"` → `v1.3`	searches a quoted pattern without quotes
`regex`	`func.*parse` → `/func.*parse/`	heuristically interprets a pattern as a regular expression, rather than literally.[6]
`language`	`python` → `language:python`	converts a pattern to a filter that restricts search to files of a particular language

remaining patterns to an `AND` expression. AQE achieves this power by feeding atomic rules to a lazy query generator. The generator applies rule transformations in *prioritized order* and iteratively attempts combinations of atomic rules in the same order. The order of generated queries bear on how alternative searches are evaluated at runtime, and we explain why this is significant shortly. To curb combinatorial explosion during query generation, we first prune rules that cannot apply to a query (where rule preconditions are unsatisfied) and bound the number of valid query alternatives to evaluate (experimentally, a threshold of 5 queries work well in practice).

Thus far, we've described rules implemented in AQE. Rules specify (only) static preconditions and transformations for generating alternative queries. A lazy generator encodes the sequence of statically valid *candidate* queries that may produce results that are helpful to the user. Merely suggesting the possible alternatives in the traditional sense may overwhelm users (if the generator produces many candidates) or produce unhelpful "no op" alternatives if those queries do not return results once they are evaluated. This is where AQE takes a step further by iteratively evaluating candidate queries, inspecting whether there are any results, and returns these to the user.

B. Implementing and taming runtime behavior

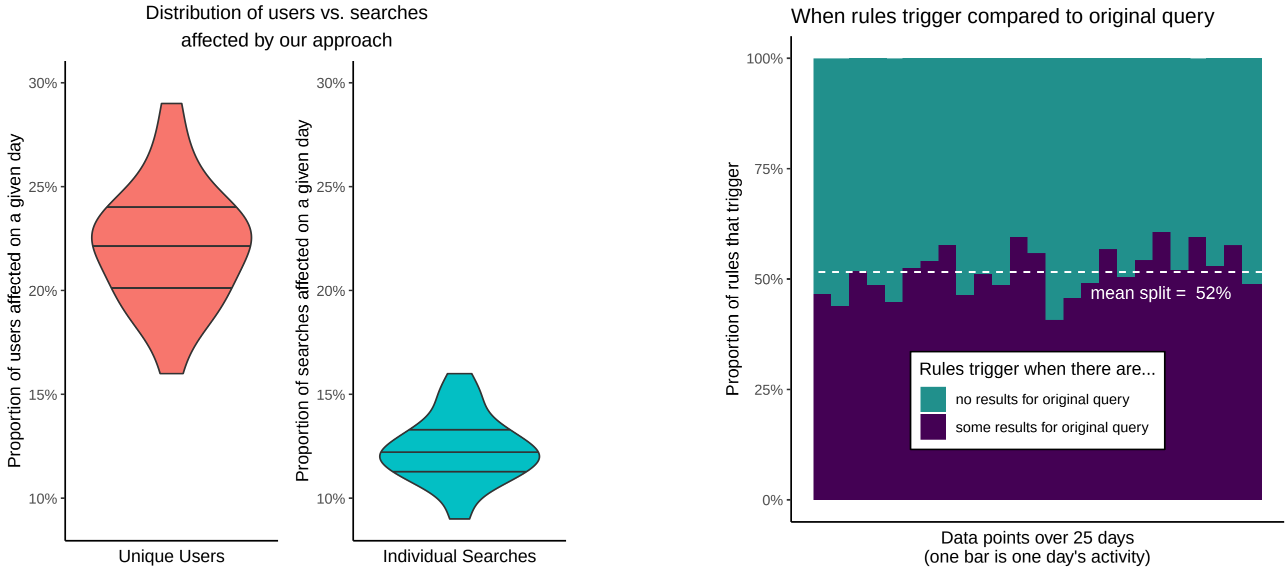
A crucial practical goal is to additionally ensure **performant runtime behavior** when evaluating alternative queries. Our backend search service is built in key ways to enable AQE to work well at runtime. First, results found ordinarily by our search engine are immediately *streamed* to the client. This has the benefit that users see results before the entire search query necessarily completes (users experience a quicker time-to-first-result than waiting for the search to complete). When evaluating alternative queries, supplementary results are streamed only *after* evaluating the original query. Our backend counts the number of results streamed by the original query, and then decides to run alternative queries if the original query returned either **no** results or if the original query returned **some** results, but fewer results than we are willing to display to the user. The threshold of results we show to the user is 500. Thus, if the original query returns 500 or more results, we do not run AQE. If less, we run AQE, which appends supplementary results corresponding to alternative queries (if any) until we reach the threshold of 500 results or exhaust the number of alternative queries to run. This behavior ensures minimal disruption with respect to the original query's meaning, and only reports additional results under the special condition where alternative query results supplement the original behavior. Equally critical, we immediately shortcircuit running AQE once the maximum threshold of results are streamed, circumventing performance issues due to long-running queries (and awaiting their outcome) or large in-memory result sets.

We evaluate queries sequentially in the order they are generated lazily. As a further step we've also decoupled query generation and evaluation such that our search architecture can run multiple alternative queries in parallel—a characteristic that helps us explore tradeoffs in performance and precision for supplementary results. We implement the evaluation order of atomic rules based on our intuition of how those rules may grow the supplementary result set. Roughly, we prefer rules that are *more particular* (or specific) to fire first, followed by more general rules that require looser conditions to apply. Table III shows the rule order in reverse, from most general (`and`) to less general (`language`). The intuition is that applying more particular rules, e.g., `language`, are likely to narrow results and produce a relatively smaller result set compared to other rules, since it has a restrictive effect on the overall search space. On the other hand, more general rules like `and` remove an ordering constraint on queries and cast a wider net over the search space. Such looser constraints tend to produce relatively larger result sets and can easily trigger the 500+ result threshold. Intuitively, if `and` rules are prioritized and produce a flush 500+ result set, we may never attempt more specific rules like `language` and miss the opportunity assist users during more particular query pitfalls.

While there are clear future opportunities to consider additional static rules or runtime behaviors, our initial feature set entailed the implementation described. To measure its effectiveness we ran an A/B search on our public code search instance.

V. EVALUATION

We evaluate our approach with an A/B test conducted on Sourcegraph.com, our publicly-available code search instance. This instance indexes over 2 million of the most common open-source repositories hosted on GitHub and GitLab. Our overall objective is to evaluate whether automatically evaluating



(a) The effect of activating AQE. On average 22% of unique users activates AQE with one or more of their searches (left). In terms of individual searches, AQE activates 12% of the time on average. At most 29% of users and 16% of searches are affected respectively, which helps forecast the magnitude of potential benefit or degradation in experience we can expect to impact with AQE.

(b) How AQE behaves compared to a user's original query. On average AQE triggers 52% of the time when the original query had **some** existing results, and 48% of the time when the original query had *no* results. Knowing the proportion of searches that yield no results is an especially appealing area to improve user experience, and 48% provides ample opportunity for AQE to activate.

Fig. 2

alternative queries help users find results they are interested in. We use *click rate* as a standard measure to gauge whether users find results they are interested in. In a typical user flow, users enter a search query and then see a list of results. They may subsequently click on a result in the list, which redirects the user to an expanded file view positionally anchored at the clicked result. We make the underlying assumption that when a user clicks on a result, it is relevant and useful to their task at hand.[7]

We can only observe a meaningful delta in click rate if Automated Query Evaluation (AQE) actually triggers for the user's query. Two conditions must be met for AQE to trigger: (1) one or more rules must apply to the original query and (2) the original query returns fewer results than we are willing to display (i.e., there is room in the web client to display more results that may be useful). Thus, as a first step to evaluating click rate, we are initially interested in whether the number of queries where AQE fires is significant at all, considering our conservative choice of triggering conditions. Our research questions are as follows:

RQ. 1: Do a significant proportion of user queries trigger AQE? If we can reject the null hypothesis that AQE has no observable effect, then we're also interested in the proportion of queries that trigger AQE. The proportion of queries that trigger AQE establish to what extent we may impact a user's search experience. Consequently, we also ask:

RQ. 2: Does user click rate differ between AQE users and the control group? If we can reject the null hypothesis that AQE has no observable effect on click rate, then we're also interested in (a) the magnitude of the delta in click rate and (b) the distribution of AQE rules corresponding to clicked results.

These research questions inform strategies to improve a user's search experience and the utility they gain from it. For example, **RQ. 1** indicates not only to what extent we might achieve a positive outcome, but also flags the possibility that AQE may apply too eagerly and produce unpredictable effects (rules are "noisy" and produce noisy results). Similarly, **RQ. 2** indicates the behavior and efficacy of various rules (if any), informs design tradeoffs to consider (apply conservative versus aggressive rules in different contexts).

A. *Experimental Setup*

Our A/B test ran for 25 weekdays (5 weeks, consistent with the range of standard practice [5]) across more than 10,000 unique users, averaging approximately 1,600 unique users per day. We activated the new automated query suggestion feature for half of the population (≈800 unique users per day), with the remaining 50% of users establishing the control group. Feature activation is consistent and deterministic per user, meaning that once a user is bucketed into either the A or B variant, they receive the same feature set over the duration of the A/B test. Users who receive the new feature variant are exposed to the search behavior and dialog box shown in Fig. 1.

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[7] See, e.g., [1] for example tasks where software developers use code search.

We collected anonymized, aggregate data over the course of the A/B test. To answer our RQs we instrumented the application to collect whether a user's query triggered AQE, which rules applied to their query, and whether they clicked on a result associated with alternative queries. Each search event is further associated with one of the two categories: (1) whether the event occurred when the user's original query returned **no** results, or conversely (2) whether the event occurred when the user's original query did return **some** results, but fewer than the maximum number of results we are willing to display. We consider these distinct scenarios to better understand the hypothetical utility of rules and result clicks. In the first category, we know that a clicked result must correspond to results generated *purely* from AQE. In the second, we know that a result click corresponds to a result set to which AQE *added* results, but due to the instrumentation complexity we do not record whether the clicked result corresponds to the original query or an automatically generated query (it may be either).

B. Experimental Results

Effect on user search experience (RQ. 1). Our results show that an average of **22%** of unique users in the experiment group trigger AQE per day. That is, on a per-user basis, at least one of the user's searches triggers AQE. In terms of all search events, an average of **12%** of individual searches trigger AQE. Fig. 2a summarizes this result. For both observations we assume normality (Shapiro-Wilk test, $p > 0.5$) and conclude significance (one sample t-test, $p < 0.5$). We observe 4.19 searches per user in the control group versus 3.95 searches per user with AQE. In terms of the *number of searches* per user, we forego a deeper analysis to meaningfully conclude whether AQE is significant: The fractional difference of 0.24 searches per user has little impact on our RQs, and we suspect there exists significant variance in usage here that would require additional instrumentation to control for (e.g., heavy users versus novice users, or even automated scripts). However, taking the overall information as a rough indicator, observing $\approx$4 searches per user suggests that in the distribution of users compared to searches (Fig. 2a), AQE has a significant probability of triggering per user, and affects one or more of a typically small number of searches.

Fig. 2b summarizes our subsequent analysis to bucket how AQE behaves compared a user's original query. Whenever a user triggers AQE we record whether their original query returned **no** results or **some** results. On average AQE triggers slightly more often when the original query produces some results (**52%**) versus no results (**48%**). Intuitively, AQE provides greater utility when the original query produces no results, since we then create opportunity for users to see or click on results that they would not have had otherwise. Our key take away is that the 48% proportion of searches in this category suggest ample opportunity to leverage AQE in the worst "no results" case.

Effect on click rate (RQ. 2). The most meaningful aspect of our experiment investigates whether our approach is ultimately helpful, which we pose by asking: How does AQE affect click rate? We observe the most compelling result when we consider searches by unique user, and whether unique users click any result at all on a given day.[8] Fig. 3 summarizes our main result. On average, on any given day, we find that users are **22%** more likely to click on a result at all compared to the baseline when AQE is active. Interestingly, Fig. 3 shows an almost uniform shift in the distribution of clicked results by user when AQE is in effect. The shift is substantial: users with AQE are more likely to click on a result *on average* than even the *best-case*, highest-probability scenario for users without it (Fig. 3).

When we consider all search events in aggregate (without respect to unique users, since our data does not associate the number of searches to individual users), the effect of AQE is more subtle, but still notable. In absolute terms, we find that the total number of clicked results relative to searches decreases slightly by 2% (two-sample t-test, $p \approx 0.04$), but we must be mindful that AQE operates by strictly adding results to what the original query produces, and especially when the original query produces no results (cf. Fig. 2b).

In other words, if users click on search results corresponding to queries that would normally return **no** results, but they click on such results with *lower frequency* than the average click rate of queries that do return results, we'll observe an overall drop in click rate, even when we are in the desirable case where users are presented with more opportunities to click results they otherwise would not have. We found this behavior indeed influences user clicks with AQE. For one, searches conducted with AQE active yield non-empty results **10%** more of the time compared to the baseline (which correspondingly yields no results). Further, **5%** of all clicked results with AQE correspond to queries that ordinarily have **no** results. In absolute terms, all clicks in this group are additive to the baseline click rate (**+5%**) in practice, because results correspond to searches that are ordinarily "unclickable". However, the click rate of AQE in the "no result" bucket is a lower **33.3%** compared to the baseline click rate at **49.3%**, accounting for an overall relative drop in click rate. Similarly clicked results corresponding to queries with **some** results account for **7.6%** of all clicks, with a click rate of **47.31%**. We found it somewhat surprising to see a slight drop in click rate for the case where AQE adds results. Here we considered how the breakdown of rules corresponding to clicks might deliver additional insight.

Fig. 4 summarizes which rules triggered a given query, broken down by whether that rule was associated with an original query that had **no** results (Fig. 4, left) versus **some** results (Fig. 4, right). Rule IDs correspond to the transformation rules in Table III. In addition we show rule `other`, a catch-all identifier other experimental rules that we anticipated would trigger less frequently (e.g., detecting whether a user wants to search commit messages versus function symbols, or converting GitHub URLs to repository filters). Rule `composite` additionally represents any composition where two or more

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[8] Note that this data is a function of our aggregation telemetry: we do not associate search events with each user, we simply count whether they clicked a result at all (not how many times they clicked a result).

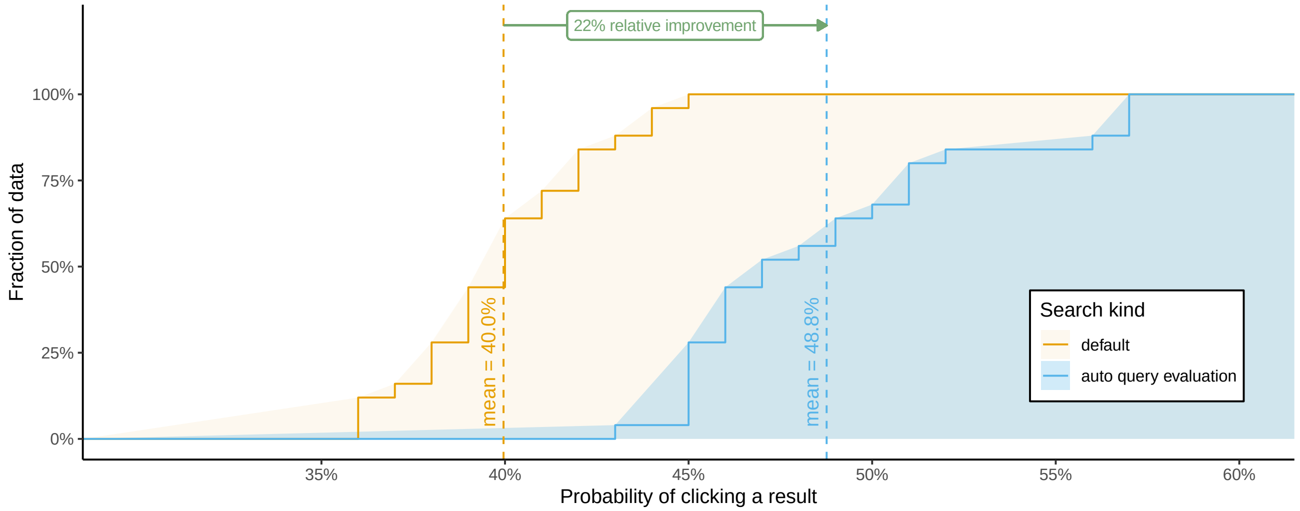

Fig. 3: Cumulative distribution function over users who click on a search result at all on a given day. Our main result shows that on average, users are **22%** more likely to click on a search result when AQE is active, relative to the baseline default behavior. There is also a notable uniform shift across the distribution, and users with AQE are more likely to click on a result *on average* than the *best-case scenario* for users in the baseline (compare the better 48.8% mean for AQE to the maximum probability of ≈45% representing all users in the baseline group).

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of the rules apply (e.g., apply the `lang` rule followed by the `regex` rule). Due to the large number of possibilities, we do not currently record each discrete combination of rules for composite queries (in future using an efficient encoding may enable us to do so).

Rule `and` triggers most often in both scenarios, where the original query returns either no results or some results. This is somewhat expected, since intuitively rule `and` requires looser properties to trigger compared to other rules: a search query needs to contain just two or more search terms like `func parse`, and the search must find results where files contain both terms. Contrast this with rules that require more specific conditions to trigger patterns (e.g., recognizing a language like `Python` for rule `lang`, or patterns containing quotes). However, we were surprised by the stark difference when comparing the distributions in Fig. 4. The proportion of clicks for the `and` is lower for the the **no** results case on average, and the difference in variance is significant (F-test, $p < 0.05$). Our data reveals that when the original query yields no results, there is a greater variation in rules that apply and corresponding results clicked (Fig. 4, left). One possibility is that the terms in the query are inherently less likely to be found together in files for these kinds of searches (i.e., the `and` rule succeeds less often with respect to code being searched). Conversely, cases where rule `and` succeeds along with the original query (Fig. 4, right) may mean the search terms overlap and share the same search space, finding multiple satisfying results. Another possibility is that this difference accounts for different kinds of users. For example, it may happen that new users who are unfamiliar with the query language click results produced by the `unquote` rule more frequently in the "no results" case, if they expect quotes to work similar to that of Google search. Segmenting these concerns is part of future work. Our main takeaway from the current data is that it is evidently worth evaluating the effectiveness of rules in these different contexts, and strategically picking the ones that are most useful contextually. As mentioned, we observed a slight drop in click rate for AQE in the case where there already are existing results. Fig 4 concretely points out that the rule most likely responsible for this change is an aggressive application of the `and` rule. This kind of information is key for testing rules and converging on a set of rules with a greater utility.

C. *Discussion and Limitations*

We were surprised by the substantial shift and impact in search and user behavior induced by AQE, considering our focus on minimizing disruption to existing behavior. One of our takeaways is that "gray area" intent with respect queries has a signficant effect on failure-prone behavior that end up yielding **no** results. We set up our experiment to segment and control for organic usage on weekdays [5], and rely on session cookies to identify unique users. The validity of our results could be affected by differing usage patterns between enterprise customers and our public, open-source instance. Additionally, usage patterns may differ between users of varying expertise. Segmenting users based on usage patterns is an area of future consideration. Implementing AQE performantly in other code search tools is an important consideration for product viability. Our evaluation shows that AQE triggers additional searches 10% to 15% of the time (inducing additional performance overhead) with the potential to assist an outsized number of

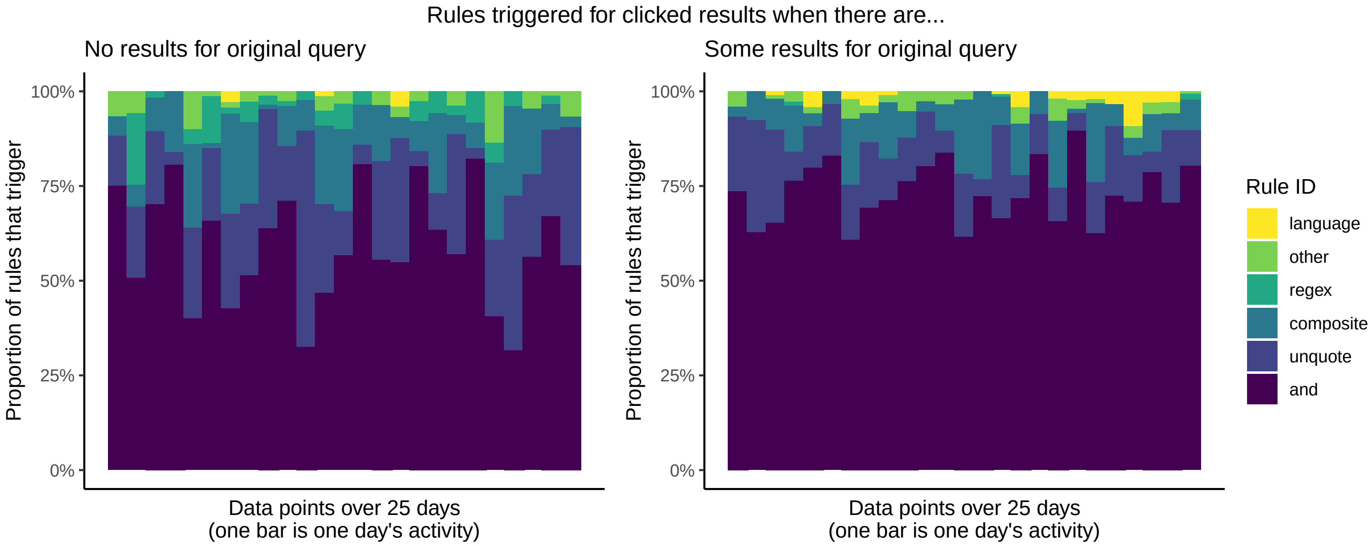

Fig. 4: Rule breakdown for clicked results. The `and` rule dominantly triggers for queries that ordinarily have **no** results (left) and queries that do have **some** results (right). However, there is a stark difference in click distribution between these two groups, with the "no results" case (left) seeing a more varied tendency to click on results across rules. The difference may be due to inherent properties of the search patterns and files being search, user profiles (new users versus familiar users), or resulting from search usage in different contexts for varying tasks.

individual users (up to 29%). While attractive in our setting, this tradeoff will depend on tool context and deployment costs.

VI. RELATED WORK

The most closely related work to ours informs how developers use code search at Google [1]. This case study covers how users interact with filters like `lang:`, and the kinds of software tasks that influence how users create and reformulate queries. Similar to our investigation, this work likewise suggests that search usage and clicks depend on varying developer contexts and query properties. In contrast, our approach delves specifically into altering the default search behavior, testing whether we can assist users in finding results by automatically attempting alternative query interpretations. In this light, AQE presents a new way to automatically reformulate queries based on known pitfalls and complexities introduced by query language design.

A recent survey covers a plethora of opportunities and challenges in code search tools [6]. Studies consider approaches to query reformulation [7], [8] and techniques that influence ranking [9]. A large body of work investigates query expansion to process natural language queries to find relevant code snippets [10], [11], [12]. In general, while academic pursuits and studies offer promising future directions for developer tooling, they do not operate with the constraint where tens of thousands of active users may be drastically or negatively impacted by new approaches, nor do they typically account for deploying a workable solution at our scale. We developed our approach in direct response to vocal feedback where users experience recurring papercuts in an already popular industrial code search tool. We found that many query papercuts stem from interactions influenced by language properties and confusion around intent and semantics. Our focus was on reconciling this language confusion with AQE, rather than a focus on increasing result relevance or ranking, or, e.g., building a natural language query interpreter. In analyzing qualitative user feedback and consequently developing AQE, we found that targeted query transformations can have a significant effect on usability and search behavior while minimizing disruption to our users.

VII. CONCLUSION

We identified unique challenges in designing a code search language and revealed how design choices in query behavior can lead to mismatches in user expectation. We developed AQE to help reconcile contradictory user expectations by automatically evaluating query alternatives and showing those results to users. We evaluated our approach over a large A/B test averaging 1,600 active users a day. We found that with AQE, users are on average 22% more likely to click on a result at all on a given weekday compared to ordinary users. Considering our focus on minimizing disruption to existing behavior, we were surprised by the substantial shift and impact in search and user behavior induced by AQE. Evidently, failure-prone cases that manifest due query language properties and apparent ambiguities can impact users extensively. We expect that investigating greater application of AQE can fruitfully assist users in avoiding pitfalls, and that its development can benefit today's code search tools at large.

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