ViCLOUD: Measuring Vagueness in Cloud Service Privacy Policies and Terms of Services

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***Abstract*—Cloud Legal documents, like Privacy Policies and Terms of Services (ToS), include key terms and rules that enable consumers to continuously monitor the performance of the cloud services used in their organization. To ensure high consumer confidence in the cloud service, it is necessary that these documents are clear and comprehensible to the average consumer. However, in practice, service providers often use legalese and ambiguous language in cloud legal documents resulting in consumers consenting or rejecting the terms without understanding the details. A measure capturing ambiguity in the texts of cloud service documents will enable consumers to decide if they understand what they are agreeing to, and deciding whether that service will meet their organizational requirements. It will also allow them to compare the service policies across various vendors. We have developed a novel model, ViCLOUD, that defines a scoring method based on linguistic cues to measure ambiguity in cloud legal documents and compare them to other peer websites. In this paper, we describe the ViCLOUD model in detail along with the validation results when applying it to 112 privacy policies and 108 Terms of Service documents of 115 cloud service vendors. The score distribution gives us a landscape of current trends in cloud services and a scale of comparison for new documentation. Our model will be very useful to organizations in making judicious decisions when selecting their cloud service.**

***Keywords*-vagueness; privacy policy; ToS; ViCLOUD; cloud service**

I. Introduction

Cloud services allow users to access computer resources on-demand and without direct active management. They provide affordable and low maintenance alternative to hosting in-house technology. While there has been a significant increase in cloud service deployment, consumers are concerned about the security and privacy of cloud data since service providers have direct access to a considerable amount of customer data that includes Privately Identifiable Information (PII). There is a risk that this PII information could be lost or stolen, either intentionally or deliberately. Additionally, cloud services are legally allowed to share consumer information, after getting consent from the consumers, with third-party vendors. They may also use an individual's data, especially in an aggregated form, to provide other services. For example, Kinsa uses deidentified temperature measurement data shared by individuals to produce a "heatmap" of human temperatures in the country. [1]

To meet the data privacy regulations and assuage consumer concerns, cloud service providers often include legal documents that detail the service functionality and data privacy policies of the service providers. Consumers and providers of cloud services sign a Terms of Services (ToS) agreement, which is a legal document that defines the rules of conduct for the customer and guarantees the availability of services and resources when the conditions are met. It is a legally binding document that is used to solve disputes between the cloud services or its customer or deny service when there is a breach of conduct. In the event of loss of PII, the legal document that protects the customers' rights is the Privacy Policy that includes policies regarding data capture, storage, transformation, and sharing with third-party vendors.

Since cloud service privacy policy and ToS are two of the most important legal documents for a customer of cloud services, its essential for consumers to clearly understand the language, terms, and conditions stipulated in them before consenting to the policies. However, these documents can often be vague and incomprehensible to the intended audience. In a 2019 study by Litman-Navarro [14] privacy policies were found to be verbose and full of legal jargon. A project in 2012 [21] ranked the ToS of popular web services based on their readability. Considering that the average user has 10th-grade fluency in English, many of the ToS documents were found to be too complicated. Data protection regulations like the California Online Privacy Protection Act (CalOPPA)[6] and the EU General Data Protection Regulation (GDPR)[23], mandate that cloud services collecting customer data must conspicuously post their privacy policy. It is also recommended by CalOPPA that privacy policies "be written in clear and concise language, be written at no greater than an 8th grade reading level". There

[1] https://healthweather.us/?mode=Observed

is no authority that enforces similar rules for ToS. However, to ensure customer trust, transparency in services' policies is of utmost importance. It is thus useful to have a system that takes as input a user-facing cloud legal document and evaluates how vague or ambiguous are the terms and rules defined by the provider. Such a system will bring us closer to automating the monitoring of cloud service policies. This is an ongoing goal of research on cloud service processes and policies [12],[11],[13].

We have developed a novel model to measure the ambiguity or vagueness in Cloud Service legal documents (ViCLOUD). This measure also helps in evaluating the relative complexity in cloud legal documents. Since "vagueness" is an abstract idea it can be subjective. A document that is easily understandable to a user with 12th-grade fluency in English might not be understandable to a user with 5th-grade fluency. So while it is hard to find an absolute measure of vagueness, we have identified objective measures of some of the factors that contribute to increasing ambiguity or vagueness in a document. Using these measures, we have developed an integrated scoring system for vagueness in legal documents. This score also helped us compare related documents and also tells us how difficult an average user might find comprehending that document. We have validated our model by applying it to 108 ToS and 112 privacy policies of 115 popular cloud services. The reported ViCLOUD scores can be used as a benchmark for complexity in legal documents of cloud services.

The rest of the paper has been organized as follows: Section II talks about Related Work and the precedent for building our model. Section III analyses the concept of vagueness in the English Language and identifies the linguistic markers of vagueness in policy literature. We established a measure of the factors contributing to vagueness and defined a scoring system for vagueness. Section IV contains details of our experimental results and Section V illustrates the results from our validation study. We conclude the paper in section VI.

II. Related Work

In our research, we focused on cloud service privacy policies and ToS that were written in English. We identified what sentences were considered vague in English and the factors that lead to a lack of clarity in its meaning. "Vagueness" is an abstract concept and is inherent in natural languages. Bertrand Russell, in his paper on "Vagueness" [24] explains that language is vague because all words- Physical-Object words, Logical words, Proper names, etc. are vague. To quote him more fully: "a word is vague if it is a word the extent of whose application is essentially doubtful; all words have an extent of application that is essentially doubtful; hence all words are vague." It is difficult to define "essentially doubtful". However, if the intended meaning is not clear, it is considered vague. As Janet Cotterill explained in "Vague Language Explored" [4] there is relatively little terminological consensus on vagueness. It is difficult to define vagueness absolutely. However, it is unanimously agreed that vagueness is the general lack of clarity or distinctness. Cheng and Warren's article in 2003 entitled *Indirectness, Inexplicitness and Vagueness*[3] concluded that 'while terminology differs, the realizations of vagueness are more consistent across the various studies'. In this work, we take some of these consistent elements of vagueness proposed by linguists to devise a measure of vagueness that can be used to judge the "understandability" of cloud related legal contracts and policies that are written in English.

Lexical ambiguity is the use of words that have multiple meanings and such words are defined as "polysemous" or "ambiguous words". The use of ambiguous words contributes to the uncertainty of meaning in text.[22] In previous works on the disambiguation of natural languages, researchers have often tried to eradicate lexical ambiguity with a static algorithm. Small et al. used a rule-based approach to resolve lexical ambiguities [22]. However, in our study, we did not eradicate lexical ambiguity but simply identified its presence. The study on "Automatic detection and resolution of lexical ambiguity in process models." by Pittke et al. [16] parsed process models and flagged words with multiple meanings as "ambiguous". We built on these studies and used the Wordnet database [15] to flag "ambiguous words".

Vagueness can also arise from a lack of specificity. "Ambiguity in Privacy Policies and the Impact of Regulation" by Reidenberg et al. [19] showed how terminologies that lack specificity and context are a determining factor for vagueness and lead to multiple interpretations of Privacy Policies. It also identified generic words such as "certain", "as necessary" etc. as vague words that reduce the clarity in privacy policies. We built on this study and identify "vague terms" or non-exclusive terms in legal documents of cloud services.

Complex sentences are also difficult to understand. According to the most recent literacy survey conducted by the National Center for Education Statistics, over half of Americans struggle to comprehend dense, lengthy texts [18]. Similar to Privacy Policy and ToS, informed consent is the ethical cornerstone of the medical community. The average reading skill of US adults is believed to be at about the 8th-grade level [5]. Hence, the American Medical Association (AMA) and the National Institutes of Health (NIH) recommended patient information materials should not exceed a 6th-grade reading level [8]. We made similar considerations for legal contracts that are important to end-users of Cloud Services. A research conducted on 64 privacy policies by Jensen et al. [10] determined the usability of online privacy policies and their accessibility to users. It was observed that the percentage of privacy policies that are accessible considering the average reading grade of the common users falls below 10%. A similar study on ToS of 500 popular websites by Benoliel et al. [1] observed that 498 of the sample ToS require a reading grade of 9 and higher.

There have been previous attempts to analyze the vagueness of technical documents in different domains. Popescu et al. [17] outlined an Object-Oriented model to reduce ambiguities in requirements specifications. It detected confusing words by parsing the document and interpreting the meaning of individual words from the lexical reference system Wordnet. The 2011 study, "A framework to measure and improve the quality of textual requirements" [9], identified 'readability' and 'unambiguity' as indicators of clarity in textual requirements. Our aim was to measure the lack of clarity in privacy policies and ToS. Hence, we used the "readability" of texts in our measure of overall vagueness.
Previous studies have developed an integrated, semantically rich Knowledge Graph (or Ontology) [7] based approach to represent the rules mandated by both PCI DSS and EU GDPR. We used a similar approach to analyze the policy documents as a set of rules and identify languages of obligation in the policy documents.

For privacy policies and ToS of cloud services, there have been studies on individual contributing factors that contribute to vagueness. There is no integrated model that takes into account all contributing factors and relatively measures vagueness in such documents. We propose a novel system that looks at the effect of all contributing factors and a scoring method to compare relative vagueness in documents. We also used the proposed system to measure vagueness in privacy policies and ToS of popular cloud services, compared them with each other, and with real user opinion.

III. Vagueness in Cloud Service Documents

A. Markers of Vagueness in Legal Documents

Vagueness or lack of clarity in a text can occur due to various reasons. There are aspects of natural language that allow sentences to be grammatically sound but still unclear in its meaning. If a statement has multiple interpretations and there is no clarification towards the intended meaning, the statement is considered vague. We analyzed how words and sentence construction choices in English affect the vagueness in statements. We identified three linguistic markers that contribute to vagueness in Cloud Service legal documents.

1) Ambiguous Words: Often in English, words can have interchangeable meaning. Such words are called "polysemous" words. Polysemy can lead to overall confusion in the meaning of a sentence. Even a non polysemous word can be differently interpreted in different contexts.
Let us look at an example. "The contract shall take effect upon execution by the customer." Here the word "execution" is a polysemous word and can mean "fulfilling an obligation" or "signing of the document". It is unclear what is the inetended meaning in this sentence. Hence it leaves room for confusion.
However certain non-polysemous words can also have multiple meanings. Let us take an example. Many privacy policies include a variant of the following statement: "The same unsubscribe process is available to a parent or legal guardian of a minor." In this sentence, the true meaning of minor is open-ended. Depending on the geopolitical location of the user, "minor" can mean individuals of different ages. Unless the meaning is explicitly mentioned in the policy, the use of the word "minor" leaves room for multiple interpretations. Hence it increases the vagueness of the policy. We define "ambiguous words" as the words whose meaning is not clear from the given context. The use of ambiguous words in a sentence leads to its vagueness. We thus counted the frequency of ambiguous words in a document and use it to measure the overall vagueness in the document.

However, we didn't consider polysemous words that have multiple meanings in different parts of speech (POS), e.g. the word "direct" has the following meanings: without intervening factors or intermediaries (adj.), with no one or nothing in between (adv.), aim (something) in a particular direction (verb), etc. Consider the sentence: "This Privacy Policy does not cover any use of Information that a Third Party Advertising Service Provider or Advertiser may directly collect from you." In this statement the POS category of "directly" is adverb. Hence it is clear that "directly" in this sentence is used in the sense "with no one or nothing in between". Hence, we only consider words that have multiple senses for the same POS as "ambiguous words".

2) Vague terms: Besides words with multiple senses, there are words in the English language that are inherently vague. Generalizing terms, such as "typically" or "generally", form an abstraction of information. It can be hard to interpret exact senses when statements include generalizing terms, e.g. "Generally, students without ID cards are temporarily enrolled." It is clear that use of such words lead to overall lack of clarity. We identified such inherently vague terms in English and refer to them as "vague terms".

A previous study by Reidenberg et al. on "Ambiguity in Privacy Policies and the Impact of Regulation" [20] identified and created a taxonomy of vague terms in privacy policies. Table I indicates the words that were identified by researchers as vague terms in 15 privacy policies from three different sectors[19]. We used these set of vague terms in our study on privacy policies and ToS of Cloud Services. Like words with multiple senses, they increase the confusion in interpreting a document. Hence, we used the frequency of vague terms in our overall measure of vagueness in legal documents.

3) Reading complexity of sentences: The average reading skill of US adults is believed to be at about the 8th grade level [5]. It is also recommended by CalOPPA that privacy policies "be written in clear and concise language, be written

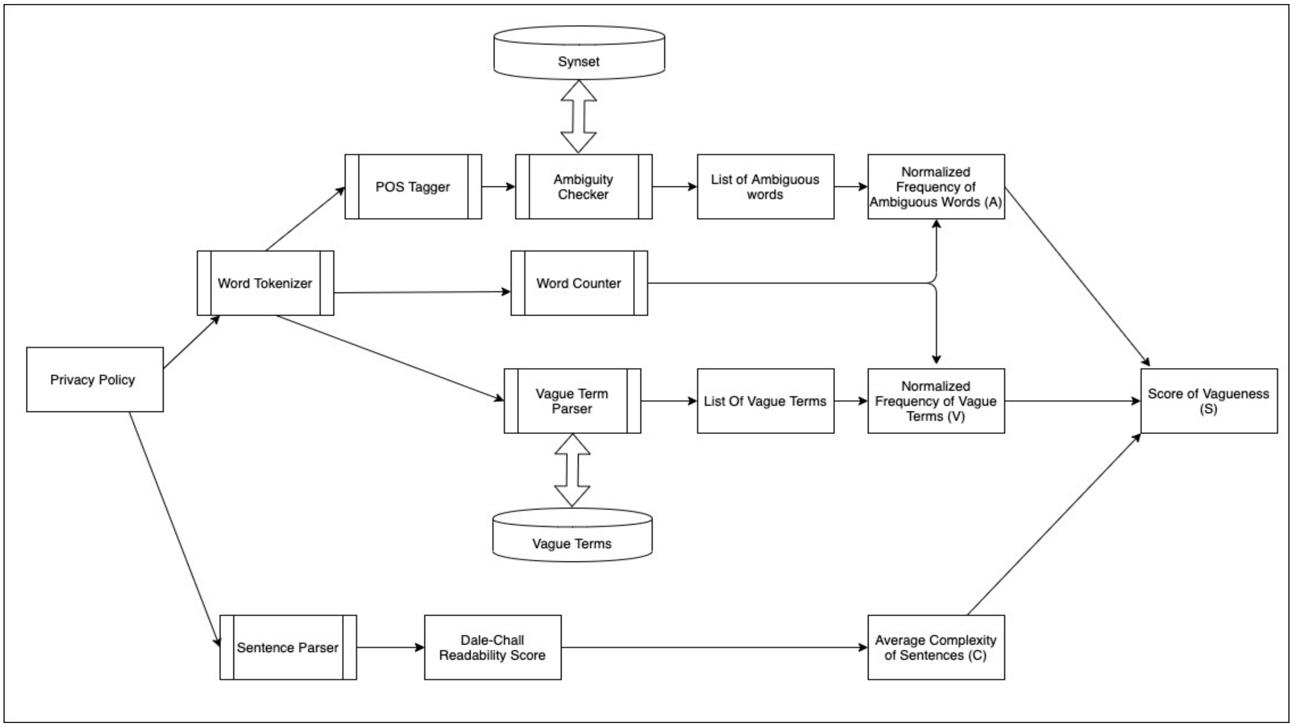

Figure 1: ViCLOUD Architecture

at no greater than an 8th grade reading level". Hence, documents that are too complex for the 8th grade reading level can be difficult to read by the average user of cloud services. Hence, overall reading complexity is an important measure for lack of clarity in documents.

The Dale–Chall readability formula[2] is a readability test that measures the comprehension difficulty that readers face upon when reading a text. It is widely used to measure reading complexity in texts. It uses a list of 3000 words that groups of fourth-grade American students could reliably understand, considering any word not on that list to be difficult. Based on the frequency of difficult words in a text, Dale-Chall readability formula assigns it a score of reading complexity. The general formula is as follows:

$$0.1579\left(\frac{\text{difficult words}}{\text{words}}\times 100\right)+0.0496\left(\frac{\text{words}}{\text{sentences}}\right) \tag{1}$$

A higher reading complexity score indicates that the document requires a higher reading grade to be easily understood. We used this reading complexity score to generate a measure overall vagueness in cloud service documents.

B. ViCLOUD: Scoring Vagueness in Cloud Service documents

Using the measures described in Section III.A, we designed the ViCLOUD model of assigning scores of vagueness to privacy policies. The overall architecture is illustrated in Figure 1.

Table I: Categories of Vague Terms [20]

Vague Terms	
Modal Verbs	'may', 'might', 'can', 'could', 'would', 'likely', 'possible', 'possibly'
Conditional Terms	'depending', 'necessary', 'appropriate', 'inappropriate', 'as needed', 'as applicable','otherwise reasonably', 'sometimes', 'from time to time'
Generalization Terms	'generally', 'mostly', 'widely', 'general', 'commonly','usually', 'normally', 'typically', 'largely', 'often','primarily', 'among other things'
Generalizing Numeric Terms	'anyone', 'certain', 'everyone', 'numerous', 'some','most', 'few', 'much', 'many', 'various', 'including but not limited to'

1) Frequency of ambiguous words: We defined ambiguous words as words that have multiple senses associated with them for the same context (or parts of speech). We used the lexical database Wordnet [15] to identify ambiguous words. Nouns, verbs, adjectives, and adverbs were grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. If a word is associated with more than

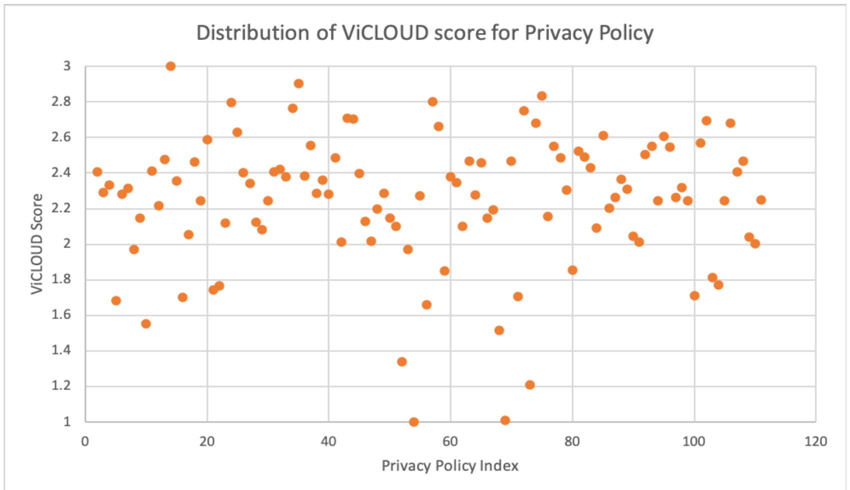

Figure 2: Distribution of ViCLOUD score in Privacy Policy dataset

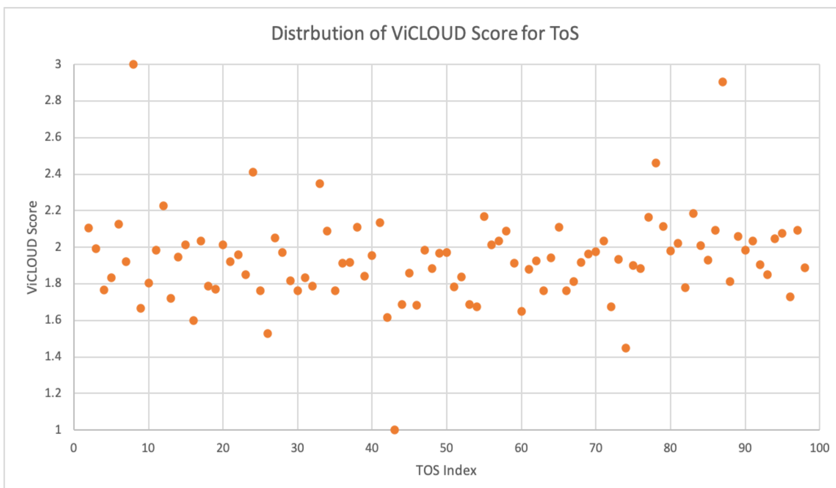

Figure 3: Distribution of ViCLOUD score in ToS dataset

one synset, it has multiple distinct meanings. We pruned the synset associations of a word by the parts of speech category of the word. If a word has more than one such association, we flagged it as 'ambiguous'.
Frequency of ambiguous words(A) =
Count of 'ambiguous' words / Total Count of Words in the policy.
The values were then normalised with a MinMax normalisation.

$$A = \frac{A - A_{min}}{A_{max} - A_{min}} \tag{2}$$

2) Frequency of vague terms: The vague terms have been identified in Table I. We counted their occurrence in the text.
Frequency of vague terms (V) =
Count of vague terms / Total Count of Words in the policy.
The values were then normalised with a MinMax normalisation.

$$V = \frac{V - V_{min}}{V_{max} - V_{min}} \tag{3}$$

3) Average Sentence Complexity: We tokenized each sentence in a document and measured the Dale-Chall readability score[2] for each sentence = DCR_i
Average Sentence complexity (C) is given by, $\Sigma(DCR_i)/N \times 10$
The values were then normalised with a MinMax normalisation.

$$C = \frac{C - C_{min}}{C_{max} - C_{min}} \tag{4}$$

4) Score of Vagueness: The overall Score of Vagueness of the document is defined as the weighted mean of each contributing factor (A, V and C). In our initial model of ViCLOUD, we assigned equal weight to each contributing factor. Thus, the overall Score was an arithmentic mean of each contributing factor. The degree of contribution of each factor can be calibrated as the weights by its weight on the measure overall vagueness.

In our study, Overall Score of Vagueness (S) for a privacy policy, is given by

$$S = \frac{w_A A + w_V V + w_C C}{w_A + w_V + w_C} \quad (5)$$

In our study, we take,

$$w_A = w_V = w_C = 1 \quad (6)$$

Figure 1 illustrates the overall architecture of the ViCLOUD system.

5) Rescaling Vagueness Score: Vagueness is a subjective constraint. We need an objective measure for the subjective opinion. We can understand how vague the average users find a document by asking them to rate its lack of clarity. The typical way to gauge user opinion is with a 5-point or 3-point rating scale. In Section V, we explain how we collected user survey using 5-point and 3-point rating scales to validate our model.

We rescaled the ViCLOUD score to ranges $[1 - 5]$ and $[1 - 3]$. To rescale a score ($Score_{old}$) from range $[min_{old}, max_{old}]$ to the range $[min_{new}, max_{new}]$, we use the rescaling formula:

$$Score_{new} = min_{new} + \frac{(Score_{old} - min_{old})(max_{new} - min_{new})}{max_{old} - min_{old}} \quad (7)$$

This gave us an estimate of the average user opinion on a 5-point and 3-point rating scale respectively. From our validation study, we concluded that the 3-point rating scale is a better estimation of the average user opinion. This is discussed in details in Section V.

In the following section we explain the experimental results of ViCLOUD scoring on 112 privacy policies and 108 ToS from 115 cloud service vendors.

IV. Experimental Results

A. Dataset

For this study, we collected publicly available Terms of Services and Privacy Policies of popular cloud service vendors. Our dataset consisted of 108 Terms of Services and 112 Privacy Policies.

We also reserved 20 ToS and 20 Privacy Policies for validation by real users. In our validation experiment, we used a pool of real users individually rating these documents. The average user used in this experiment were regular users of cloud services, are all graduates in STEM fields and had English education upto 10th Grade or higher. According to CalOPPA, privacy policies should be readable by someone with 8th grade fluency or higher. Our pool of validators was thus a good representation of the average readers of cloud service policies and agreements.

Table II: Minimum and Maximum values for A,V, C and S

	ToS Dataset	Privacy Policy Dataset
A_{min}	0.60621	0.38709
A_{max}	0.76165	0.86037
V_{min}	0.0	0.0
V_{max}	0.29222	0.354
C_{min}	0.015	0.76087
C_{max}	1.958	1.401
S_{min}	0.05116	0.26362
S_{max}	0.69786	0.67168

B. Results

1) Privacy Policy Dataset: The ViCLOUD model scored vagueness in 112 sample privacy policies of Cloud Services. Figure 2 illustrates the distribution of ViCLOUD score for 112 privacy policies. We also validated the scores assigned by the ViCLOUD model with real user rating. The results from our validation studies are discussed further in Section V.

2) ToS Dataset: A similar experiment was run with 108 sample ToS of Cloud Services. Figure 3 illustrates the distribution of ViCLOUD score for 108 ToS. We also validated the scores assigned by the ViCLOUD model with real user rating. The results from our validation studies are discussed further in Section V.

The minimum and maximum values of individual contributing factors (A,V and C) and the total score (before rescaling) in both datasets have been included in Table II. This gives an idea of the range of scores in privacy policy and ToS dataset.

V. Validation

In order to validate the results of ViCLOUD model, we compared the vagueness rating assigned to test ToS and privacy polcies by ViCLOUD with real user opinion. We selected 10 ToS and 10 Privacy Policies from our dataset; we will call this validation dataset A. We selected another 10 ToS and 10 Privacy Policies from our dataset; we will call this validation dataset B.

We collected a group of 20 regular cloud service users. All users in this experiment had English education upto 10th Grade or higher. According to CalOPPA, privacy policies should be readable by someone with 8th grade fluency or higher. Our pool of validators consisted of graduate students in computer science and workers in the IT industry. Hence, they were a good representation of the average readers of cloud service policies and agreements.

We asked our validators to rate each document from our validation dataset A out of 1-5, based on its lack of clarity. We provided the following definitions of the ratings to the user. Rating 1 means least vague and easiest to read. Rating

(a) Privacy Policy Dataset

(b) ToS Dataset

Figure 4: ViCLOUD Score[1-3] versus User Rating in Validation Dataset B

2 means slightly more vague but still readable. Rating 3 means moderately vague and moderately readable. Rating 4 means more vague and hard to read, but user is still able to gather some information. Rating 5 means most vague and was hardest to read.

We then asked our validators to rate each document in our validation dataset B out of 1-3, based again on its lack of clarity. We provided the following definitions of the ratings to the user. Rating 1 means least vague and easiest to read, rating 2 means moderately vague and moderately readable and rating 3 means most vague and hardest to read.

We noticed that users are not comfortable with the level of granularity in the 5-point rating scale. The mean of the user ratings for most documents fell in the [2-3] window with a high variance (0.7329). With the 3-point rating scale, the users agreed more with each other, as indicated by the low variance (0.4217).

For each document in Validation Dataset A and B, we took the average of the rating of all validators for that document. Let D be any document in our dataset. The error margin of the average user rating for D = 0.75 $\times$ standard deviation of user ratings for D.

For validation dataset A, we compared the average of user rating to the ViCLOUD score for that document in range [1-5]. For validation dataset B, we compared the average of user rating to the ViCLOUD score for that document in range [1-3]. We used the Pearson correlation coefficient to measure the correlation between ViCLOUD score and average user opinion. Correlation coefficient = 0.6 or higher indicates a moderate positive correlation between two variables. Correlation coefficient = 0.8 or higher indicates a strong positive correlation between two variables.

A. *Results*

Table III and IV respectively reports the ViCLOUD score and the average user rating for privacy policies and ToS in dataset B. Figure 4 reports the ViCLOUD Vagueness Score in Range [1-3] versus average User Rating with the error margin for validation dataset B.

The ViCLOUD score fell within the error margin of the average user rating for 17 out of 20 documents in validation dataset B. The difference (D) between the ViCLOUD score and user rating for a document in dataset B is given by:

$$D = ViCLOUD\ score\ -\ Avg.User\ rating \quad (8)$$

The average value of D in dataset B was 0.1028. This is the bias in ViCLOUD score. The positive value indicated that the ViCLOUD score slightly overestimated the average user rating. However the absolute value of the bias was small. Thus our ViCLOUD score was a close estimate of the average user rating.

Minimum value of D was -0.4542 and maximum value of D was 0.4694. This indicated that the bias in ViCLOUD score was consistently distributed in the range (-0.46, +0.46). This meant that the ViCLOUD score was a precise estimate of the average user rating.

The pearson correlation coefficient for ViCLOUD score in range [1-3] for privacy policies was : 0.8153. The pearson correlation coefficient for ViCLOUD score in range [1-3] for ToS was : 0.8217. This means there was a strong positive correlation between ViCLOUD score and average user rating.

We also experimented with ViCLOUD scores in range [1-5] for dataset A. However, as mentioned earlier, the users were not comfortable with the level of granularity in the 5-point scale. This is indicated in our results.

Table III: ViCLOUD Score versus Average User Rating in Privacy Policy

Cloud Service Vendor	ViCLOUD Score	Average User Rating
Amwell	2.28264	2.16
c3	2.05342	1.89
Darktrace	2.12235	2.17
Dropbox	2.90467	2.5
Icertis	2.19832	1.83
Jfrog	1.96947	1.5
ncino	2.37911	2.83
Sitecore	2.61031	2.5
TripActions	2.60447	2.67
vts	1.81496	1.5

Table IV: ViCLOUD Score versus Average User Rating in ToS

Cloud Service Vendor	ViCLOUD Score	Average User Rating
Braze	1.59931	1.38
Ionic	1.68326	1.63
Lookout	1.88372	1.76
talkdesk	1.98074	1.76
Tanium	2.02237	2.26
Thoughtspot	1.78102	1.5
Toast	2.18354	2.13
TripActions	2.00945	1.78
Turbonomic	1.92897	2.13
UIPath	2.09138	2.25

The ViCLOUD score fell within the error margin of the average user rating for 6 out of 20 documents in validation dataset A.

The pearson correlation coefficient for ViCLOUD score in range [1-5] for privacy policies was : 0.60047. The pearson correlation coefficient for ViCLOUD score in range [1-5] for ToS was : 0.67959.

This indicated a moderately strong positive correlation between ViCLOUD score and average user rating in range [1-5]. However, the ViCLOUD score in range [1-3] is a better estimate of the average user rating.

We should mention here that to capture the entire spectrum of cloud service users and their expectations, a larger sample set of individuals is required. We are working on testing with a larger population of cloud service users to make more rigorous conclusions from our study. But our current results indicated that ViCLOUD scores have a high correlation with the average user opinion for cloud service legal documents.

VI. Conclusion

Cloud Services are steadily increasing in popularity. Security and privacy remain an important concern for cloud service consumers. Privacy policy and ToS are two of the most important documents that assure trust between cloud service providers and clients. It is extremely important that policies and agreements are understandable to the end-user. The writers of such documents must take care to make them transparent and usable. We propose the ViCLOUD model that can automatically detect relative vagueness in such documents and analyze privacy policies and ToS. An important goal of ongoing research in Cloud Services is the automation of policy creation and monitoring. The ViCLOUD model brings us closer to the goal. We used the ViCLOUD model to measure vagueness in the language of privacy policies and ToS of 115 popular cloud service vendors. The writers of new policies can judge the quality of their text by measuring the vagueness in their document and comparing it with our reported scores. Our study can be generalized to measure vagueness in any customer-facing legal documents or service contracts. For example, it can be used to analyze the clarity in regulatory documents, service level, and end-user agreements. We can also merge the ViCLOUD model with a system that assures regulation compliance to completely automate qualitative analysis of policies.

VII. Acknowledgement

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