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Can't Understand SLAs? Use the Smart Contract

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***Abstract*—A Service Level Agreement (SLA) is a special kind of legal contract that binds a vendor to its customers where the vendor commits to provide certain services in exchange for certain payment from the customers. On the other hand, a Smart Contract is a contract that is a computer program that also binds multiple parties into given agreements but is a set of a precise rules and is self-enforceable and self-executable. Since almost all legal contracts are ambiguous by nature and are complex to read and understand, we perform a novel study on how we can replace the traditional vague legal contract with the smart contact and the effect of the ambiguity on the smart contract by performing a thorough analysis on SLAs by measuring their ambiguities in various aspects. We take several samples of real SLAs from six different popular broadband vendors. We use four random SLAs to train the machine learning model to classify and then detect ambiguous words in two unseen SLAs which were the SLAs of Ziply Fiber and CenturyLink. As different people form different interpretations while reading the ambiguous legal contracts, we generate various human interpretations from the machine detected ambiguous words and convert all those generated interpretations into Smart Contracts to perform testing in Ethereum-based Blockchain to identify the most ambiguous as well as accurate interpretation of the SLA. From our analysis and observation, we were able to find out the most ambiguous interpretation of SLAs and we concluded that the SLA of Ziply Fiber was more ambiguous in general compared to the SLA of CenturyLink. Moreover, our proposed approach to detect ambiguous terms and to translate an ambiguous legal contract to a smart legal contract using a formal language to measure the degree of ambiguity can be extrapolated and replicated to legal contracts from other types of industries as well.**

***Index Terms*—Smart contract, service level agreement, SLA, ambiguity, complexity, smart legal contract, blockchain, ethereum, clauses, interpretations, ambiguity index, machine learning**

I. Introduction

A Service Level Agreement (SLA) is a legal contract between a vendor and its customer which defines the quality of service that the vendor promises to provide to its customers in exchange for their subscription and payment [1]. If the vendor fails to provide the level of service to its customers that have been defined in their SLA then the vendor will be penalized and they will have to provide the compensation to the customers that are also defined in the SLA. In other words, SLA is viewed as an important component of a technology vendor's legal contract.

However, since an SLA is also a type of traditional legal contract [2], it is full of ambiguous terms and legal jargons that makes it hard for the vendor's customer to understand the precise meaning. Oftentimes, we hear and see many reviews, news and incidents where customers complain against ISPs about not getting their internet service in exchange for what they are paying for [3], [4]. We have also heard customers spending their time and money to request compensation and service credit to their vendors. However, due to the ambiguous and equivocal nature of the SLA, it becomes difficult for the customers to get their refund back.

A legal contract is ambiguous when a specific term, word, phrase, or definition is not precise and hence results in multiple meanings [5]. Since most SLAs are ambiguous too and a lack of a precise set of metrics by which the service is measured as well as the indemnification clause results in multiple interpretations when multiple people from different linguistic backgrounds and experiences read them. As a result, the customers always have a hard time getting their compensations back from the vendors when they do not get the service they have subscribed for due to the absence of self-enforcement property and precise usage of words.

On the contrary, a Smart Legal Contract or a Smart Contract (SC) is a kind of contract where the agreements are self-enforcing and are embedded in computer code that is managed by the blockchain [6]. There are a clear and precise set of rules under which the parties involved in the smart contract agree to interact with each other. If and when the predefined rules that are written in the smart contract as code are met, there will be automatic enforcement of the agreements.

Ambiguity is an important issue when formalising contractual clauses, and we propose a formal method to find out ambiguous terms in SLA contracts using machine learning and then convert those ambiguous SLA contracts into Ethereum-based smart contracts. Thus, the main problem definition of this paper is how can we analyze and compare the ambiguous nature between different SLAs, particularly, broadband vendors' SLAs that are full of vague words that result in multiple interpretations for different people. Besides, we also discuss how can we convert these ambiguous SLA contracts into non-ambiguous and smart contracts that can be used in Ethereum-based Blockchain as the Blockchain is decentralized, distributed and also eliminates the need for middlemen such as lawyers and legal attorneys.

In spite of the fact that there has been extensive research

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going on for the smart contracts in recent years, the study specifically, on the ambiguity in legal contracts and conversion of the legal contracts to smart legal contracts considering ambiguity in legal contracts as the main factor has not been exhaustive. Although there have been several types of research on ambiguities and types of ambiguities separately, there has not been any research so far on various kinds of legal contracts and SLAs and how we can convert these legal contracts and SLAs into smart contracts, considering ambiguity as the main challenge. There has been a study done on how an SLA can be converted into a smart contract that can be used in the Blockchain to reduce manual effort to claim compensations in [7], however, the authors have not described the ambiguities and legal jargons that we see in the SLAs and how those ambiguities were considered while converting the SLA into the smart contract. In [8], the authors talk about the SLA management system but lack the research on how we can convert an SLA into a smart contract. Also, only the basic functions of the SLA Management System have been studied. Similarly, the authors talk about how they proposed a new SLA management framework that uses two-level blockchain architecture and how an SLA is transformed into a smart contract in [9] but fail to include the concept of ambiguous requirements that can cause issues while writing a smart SLA. In [10], the authors have proposed a blockchain-based method to assess SLA compliance but have rules out the ambiguities found in the SLA. Likewise, in [11], the authors have proposed a system that uses Blockchain which claims the compensation process can be kept safe and reliable but again lacks the discussion of the ambiguous nature of SLA.

II. Relationship between a Traditional Service Level Agreement (SLA) and a Smart Contract

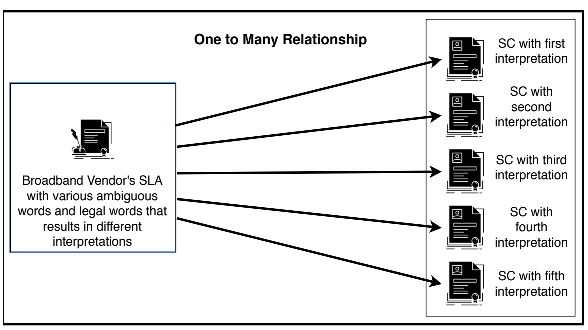

Fig. 1. One to many relationship between a SLA and smart contract

A Service Level Agreement (SLA) is written by a vendor but it is also written so that the customers can measure that the service they are getting is how it is exactly defined in the SLA. Unfortunately, an SLA consists of affluent of ambiguous, vague, and legal terms. Hence, SLA results in various interpretations when different customers read them because of their different experiences and knowledge. An SLA drafted by the legal department of a vendor is written in such a way that is full of jargon terms that only the people who are involved in legal aspects can understand the SLA. Also, the service metrics that are defined in the SLA which describes how much service and what kind of service the customers are expected to get after they subscribe for it are not clear enough for the customers to understand. In addition, even though the service metrics are written as clear as possible, there will still be plenty of words such as *'may', 'might', 'reasonable', 'best efforts', 'most likely'*, and so on in the indemnities section when it comes to giving the compensation back to the customers for bad service. Therefore, as shown in the Fig. 1, due to the presence of ambiguous words and structure in the SLA contract, different people perceive the same contract differently.

These kinds of ambiguous terms as well as the way the service metrics are defined in the SLA creates multiple interpretations. For example, one customer from different background and experience might understand the same SLA differently than the other customer who reads it. The main cause of these multiple interpretations from the same SLA is the way it is drafted and the ambiguous words contained in it. On the other hand, a smart contract is clear, precise, and straightforward. In Fig. 1, we can see the one to many relationships between an SLA contract and a smart contract. This figure describes the type of relationship between a traditional SLA contract and a smart contract and how one SLA can be interpreted in various ways due to the ambiguous words present in it. Hence, several different versions of the smart contract can be translated from an ambiguous SLA which is written in vague natural language. The more ambiguous an SLA is, the more interpretations it will have and the more possibility of generation of different interpretations of smart contracts. *Source of the different interpretations were collected from the random students in the university who were asked to read the SLA contracts during the survey.*

III. Methodology

We have divided our entire methodology into six phases as shown in Fig. 2 and Fig. 3.

In our first, second and third phases as shown in Fig. 2, we read the texts in the two SLAs and use binary classification to classify the ambiguous words from non-ambiguous words by using machine learning. Apart from being a part of future work and research, the reason machine learning is used instead of manual hand-picking ambiguous words and phrases is that we wanted to automate the extraction process of ambiguous words and phrases and evaluate the performance. Therefore, in our first phase, we gather different SLAs from different vendors but from the same industry so that we can create a training dataset for the machine to learn the kind of vague words being used in the SLAs. We have gathered six different SLAs from six different popular ISP (broadband) vendors which are AT&T [12], Verizon [13], Spectrum [14], T-Mobile [15], Ziply Fiber [16], and CenturyLink [17]. *The reason we decided to choose all the SLAs from ISP vendors and not mix from other vendors such as insurance companies was for a couple*

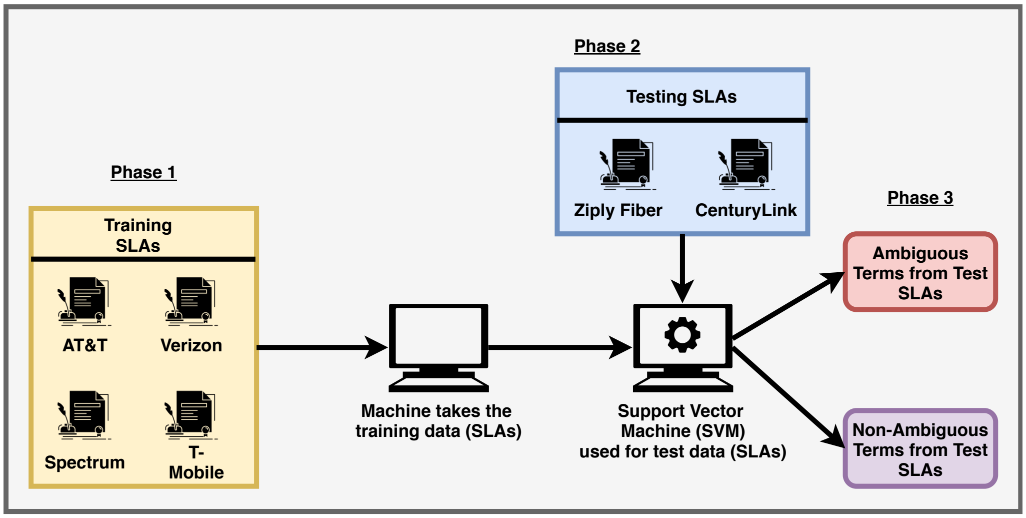

Fig. 2. Selection of six SLAs from six different vendors from the same industry and categorizing them into train and test data sets in Phase 1 and 2 and using Support Vector Machine (SVM) to detect and classify ambiguous and non-ambiguous terms from test data, i.e, Ziply Fiber and CenturyLink in Phase 3.

of reasons, primarily to get unbiased results and to translate the SLAs of ISP into the Ethereum-based smart contracts so that customers would benefit from automated compensation system and would not have to face any difficulty to get the indemnities, penalties, and compensations when they do not get their services as they were promised in the SLA contract.

We have categorized the SLAs of AT&T, Verizon, Spectrum, and T-Mobile as the training dataset while Ziply Fiber and CenturyLink were categorized as testing dataset. There were not any hard-and-fast rules to decide what SLAs are going to be as training dataset and what SLAs are going to be testing dataset. The selection of both the training and testing SLAs are done randomly. We created a script to read all texts in the SLA documents, tokenize all the words present in the documents, and finally prepared the training dataset by labeling the tokens manually as ambiguous (1) or non-ambiguous (0).

In Phase 2, we classify the SLAs of Ziply Fiber and CenturyLink as test SLAs meaning all the words were extracted

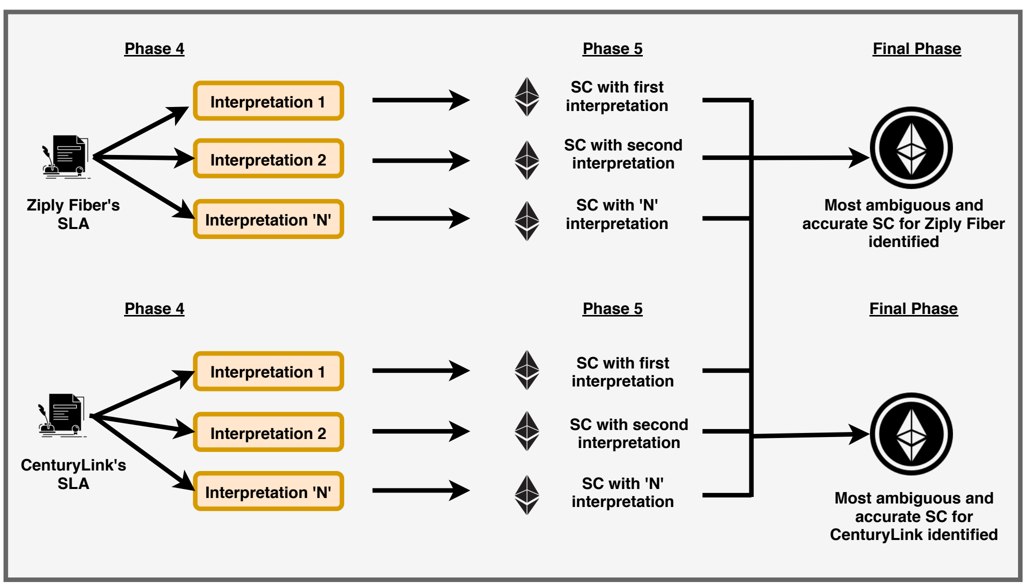

Fig. 3. Generation of all possible different interpretations of both test SLAs in Phase 4, translation of all generated interpretations from both ambiguous test SLAs into their respective smart contracts in Phase 5, and comparison and identification of the most ambiguous and accurate interpretation from each test SLA along with the most ambiguous and accurate SLA out of the two in Final Phase.

from these two SLAs were used to prepare the test dataset. Support Vector Machine (SVM) [18] was used to train the model for it to perform binary classification and detect the ambiguous words from non-ambiguous words as shown in Phase 3 of Fig. 2. After experimenting and testing with other common machine learning algorithms such as Random Forest, Decision Tree and kNN, we got the highest accuracy from SVM. As a result, we decided to use SVM for binary classification of ambiguous words in test data, i.e., tokens from Ziply Fiber's and CenturyLink's SLA contracts.

As shown in Phase 4 of the Fig. 3, after we finish detecting all the possible ambiguous words and phrases in our two test SLAs (Ziply Fiber and CenturyLink) using machine learning, we manually generate different possible interpretations from those machine detected ambiguous terms as shown in Phase 4. One of the main objectives of this study was to create as many as possible human interpretations people will have while reading the SLAs of the ISP vendors, convert all the interpretations into the Ethereum-based smart contract, and finally find out which version or the interpretation of the smart contract is more ambiguous and accurate along with finding which SLA in average is more ambiguous. The classification or detection accuracy of the model while classifying the ambiguous words in Ziply Fiber's SLA was 85% and in CenturyLink's SLA was 79%. Although increasing the accuracy is our top priority and part of our future work, we have considered only those ambiguous words that the machine has detected successfully to generate various interpretations for translating those interpretations into their corresponding smart contracts. We translate all those generated interpretations from the ambiguous words that were detected using machine learning into their respective smart contracts as shown in Phase 5 of Fig. 3. Finally, as shown in Phase 6 or the final phase in Fig. 3, we perform various testings of the translated smart contracts of all the interpretations of both SLAs and we find out what interpretation of each SLA and what SLA as a whole is the most ambiguous as well as the most accurate one.

Fig. 4, 5, and 6 describe Phase 4 of our methodology in more detail. The figure that we see in Fig. 4 is the control flow graphs that we generated from the Ziply Fiber's SLA and CenturyLink's SLA considering only the ambiguous words that the machine detected after classifying the ambiguous from non-ambiguous terms. We manually generated control flow graphs of these vendors so that we can also generate all possible special case interpretations from these control graphs. The control graphs in Fig. 4 explains how vague the SLA of Ziply Fiber and CenturyLink is by portraying multiple branches in the control graph. We have named this version of the control graph as **root control graphs** as this was our first

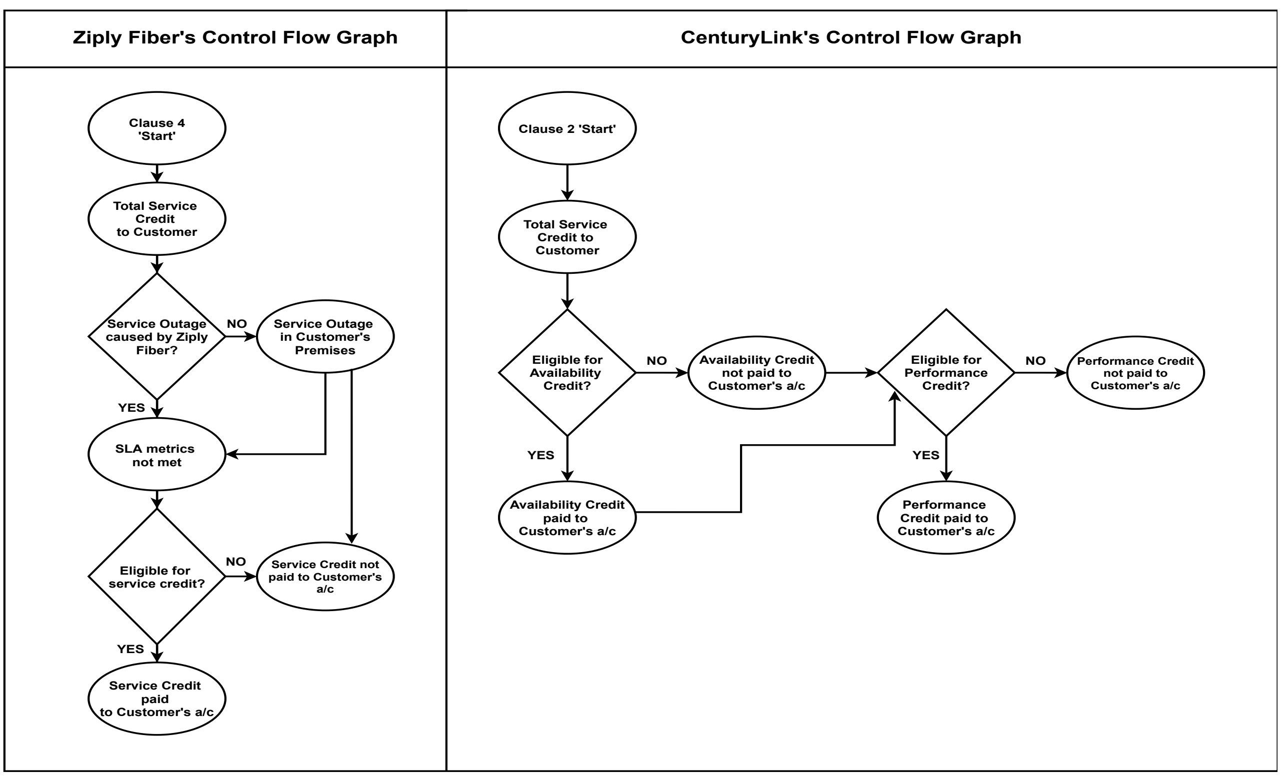

Fig. 4. Root control flow graphs of all the events from Ziply Fiber's and CenturyLink's SLA. From these control flow graphs, other five special case interpretations for Ziply Fiber's SLA and four special case interpretations for CenturyLink's SLA will be generated.

step to derive the control flow graph from the Ziply Fiber's and CenturyLink's SLA contract. The control graphs from Fig. 5 and 6 are named as **special case interpretation control graphs** as these are generated further from the root control graphs.

The sentences present in the Ziply Fiber's SLA contract such as *"In the event of a Service Outage, Customer may be entitled to a credit against the applicable On-Net Service MRC"* and *"Credits do not apply to Service Outages caused, in whole or in part, by one or more of the following."* increases the degree of ambiguity. Here, the words such as *"may"* and *"in whole or in part"* lead to more than one interpretations of the whole SLA of Ziply Fiber because these are permissive terms. It also describes different actions and events that might take place depending on the understanding of the customers who read the SLA. Hence, we first generate the root control graph of Ziply Fiber's SLA as shown on the left-column of Fig. 4 as well as CenturyLink's root control graph as shown on the right-column of Fig. 4. Hence, this would be the case of how the SLA will look like where there are multiple *"yes"* and *"no"* because of the involvement of ambiguous words which results in multiple branches in the control flow graph.

From Fig. 4, we further generate more special case interpretations. All 5 of them for Ziply Fiber are shown in Fig. 5. Hence, Fig. 5 shows how we have generated other interpretations further from Fig. 4. Similarly, Fig. 6 shows the ambiguous nature of CenturyLink's SLA as well by portraying multiple possible branches the decisions, events, and actions can have. Fig. 6 only has four interpretations as CenturyLink's SLA had less nodes, edges and connected nodes. It was the first control graph that we derived from the SLA. The sentence such as *"If Service performance falls below the thresholds provided in Table 2.0 and CenturyLink is unable to rectify the performance of the Service(s) at the Affected UNI within 30 business days then Customer may be eligible for a Performance Credit for Service degradation subject to the rules and exclusions provided in this agreement."* along with other vague sentences are used in CenturyLink's SLA which allows customers to form multiple interpretations further that we have discussed in Fig. 6.

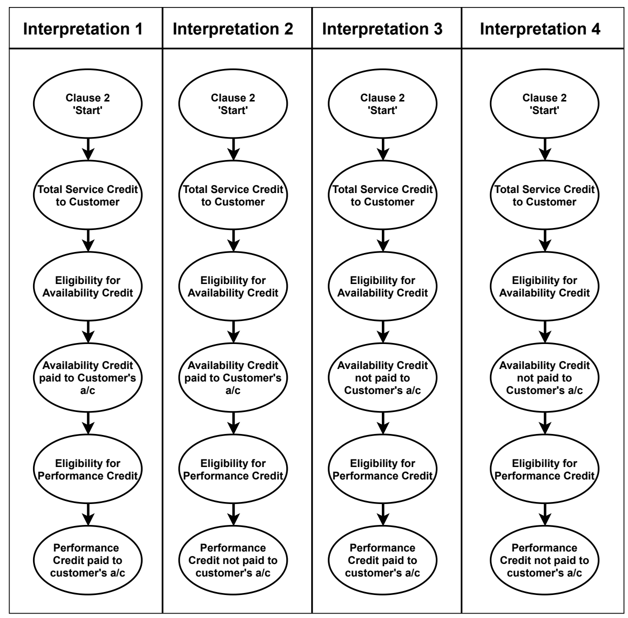

Fig. 6. Derivation of five special cases of interpretation from Ziply Fiber's Control flow graph.

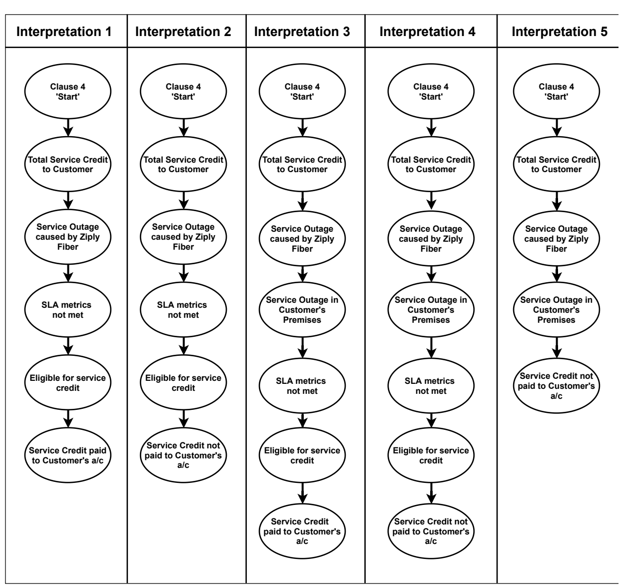

Fig. 5. Derivation of five special cases of interpretation from Ziply Fiber's Control flow graph.

In Fig. 6, we have four possible special case interpretations that can be generated from Fig. 4's root control flow graph (right-column). This further generation of interpretations was possible due to the usage of permissive and ambiguous words in CenturyLink's SLA. This case is similar to the case of Ziply Fiber's SLA. If mandatory words would have been used instead of permissive and ambiguous words, then the root control graphs in Fig. 4 would be more straight forward without different branches. Once we derived and generated all possible special cases interpretations further from Ziply Fiber and CenturyLink's root control flow graph as shown in Fig. 4, 5 and 6, we translated both the root control graphs and special case control graphs from both vendors into their respective smart contracts.

IV. Ambiguity and complexity measurement by Smart Contract deployment

We translated the root control graphs from Fig. 4 to analyze which vendor has more ambiguous SLA in general. We translated the control flow graph of Ziply Fiber and CenturyLink into their respective SLA and deployed their smart contract in Ropsten Testnet 10 times each. As we can see in the Fig. 7, the

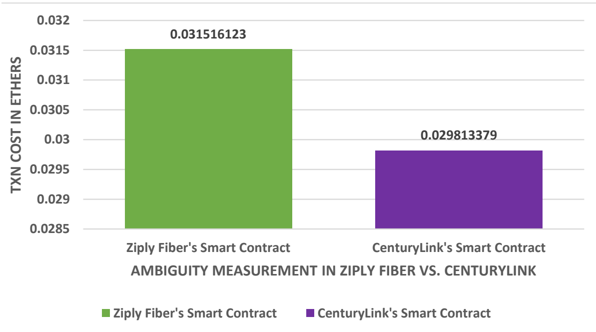

Fig. 7. Comparison of the ambiguity in SLAs from two different vendors which shows that Ziply Fiber's SLA is more ambiguous than CenturyLink's SLA.

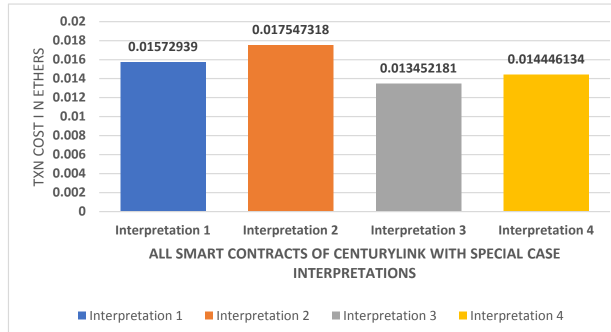

Fig. 9. Comparison of average TXN cost of 4 different special case interpretations of CenturyLink's Smart Contract for the measurement of ambiguity and complexity.

TXN cost of Ziply Fiber was 0.031516123 ETH. However, as the size of the control flow graph for CenturyLink was small and had less number of interpretations compared to Ziply Fiber, the TXN cost for CenturyLink was just 0.029813379 ETH.

Then we deployed all five special case interpretations of the smart contract of Ziply Fiber 10 different times in Ropsten Testnet. We have made the comparison of transaction (TXN) costs of all smart contracts with their respective interpretations. Fig. 8 shows the average of all the registered TXN costs of all five special case interpretations of Ziply Fiber's smart contract in Ropsten Testnet. Interpretation 1 had the average TXN costs of 0.024063215 ethers (ETH). Similarly, Interpretation 2 had average TXN cost of 0.021482481 ETH. Likewise, Interpretation 3 and 4 had 0.020106104 ETH and 0.025117192 ETH respectively. Interpretation 5's average TXN cost was the lowest because of its control flow graph size, i.e., 0.014882172 ETH. We observed that all these TXN costs of their respective interpretations correlate to their size of control graphs as well.

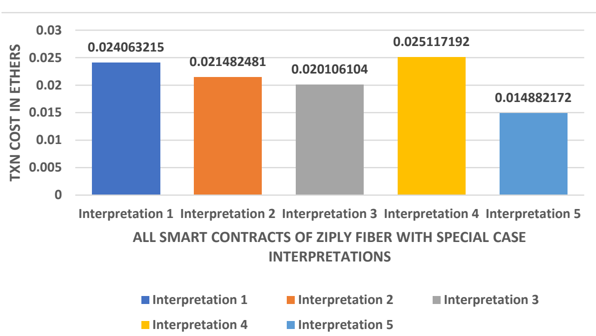

Fig. 8. Comparison of average TXN cost of 5 different special case interpretations of Ziply Fiber's Smart Contract for the measurement of ambiguity and complexity.

Similarly, we deployed all four special case interpretations of the smart contract of CenturyLink 10 different times as well in Ropsten Testnet. If we take a look at Fig. 9, we can see that the average TXN cost of Interpretation 1 is 0.01572939 ETH. Likewise, the TXN cost of Interpretation 2, 3 and 4 are 0.017547318 ETH, 0.013452181 ETH and 0.014446134 ETH respectively.

From our study, we found that the reason Ziply Fiber consumed more TXN cost than CenturyLink was because it is more ambiguous. Ambiguity is directly proportional to the complexity of the smart contract which means if the ambiguity of a certain interpretation rises, the lines of code along with the program complexity will also rise which will result in the increment of the TXN and gas cost. As we can also see in Fig. 4 and 5, the control flow graph of Ziply Fiber was more complex and had more number of interpretations. The main reason for this was the ambiguous nature of Ziply Fiber was more compared to the CenturyLink's smart contract.

Therefore, from this observation, we can say that if a particular interpretation is more ambiguous in nature, it is more complex in the control graph as well. In addition, while translating the control graph into the smart contract, due to the SLA's ambiguity as well as complexity, the smart contract of that very SLA consumed more TXN and gas cost as we can see in Fig. 7, 8 and 9.

V. Ambiguity (Uncertainty) and Complexity Measurement by Entropy and Cyclomatic Complexity

To corroborate our evaluation of the proportional relationship between ambiguity and TXN costs, we have also studied both entropy and cyclomatic complexity of Ziply Fiber's and CenturyLink's SLA along with their each interpretations which helped us to find their respective ambiguity indexes. We have used Shannon's Entropy and McCabe's cyclomatic complexity to find the uncertainty and complexity of both vendors' SLA. We have used the control flow graphs from Fig. 4, 5, and 6 to find the entropy and cyclomatic complexity. The Shannon's entropy measures the average level of information and uncertainty which is in vavriable's possible's outcomes. Similarly, cyclomatic complexity measures the complexities and the total number of linearly independent paths of a program.

A. Shannon's Entropy:

The Shannon's entropy [19] is defined as:

$$H(X) = -\sum_{i=1}^{n} P(x_i) log P(x_i) \quad (1)$$

Where, $H(X)$ is the entropy of X, $\sum_{i=1}^{n}$ is the sum over variable's possible values, *log* is natural logarithm, $x_1 ...., x_i$ are possible outcomes and $P(x_i)$ is the probability of the occurrence.

We calculated Shannon's Entropy for both control flow graphs of Ziply Fiber and CenturyLink from Figure 4. To calculate Shannon's entropy, we considered the number of special case interpretations each SLA (root control graph) can generate. For example, the number of special case interpretations from Ziply Fiber (Fig. 5) is 5. Hence, each special case interpretation is assumed to have 1/5 probability of occurrence. Likewise, the number of special case interpretations from CenturyLink (Fig. 6) is 4. Therefore, in this scenario, each special case interpretation is assumed to have 1/4 probability of occurrence. We found out that entropy for Ziply Fiber was 1.6094 and for CenturyLink was 1.3863 as shown in Table I and II. From this, we can say that that control flow graph and hence, the nature of Ziply Fiber is more uncertain and ambiguous than SLA of CenturyLink.

TABLE I
ENTROPY MEASUREMENT OF ZIPLY FIBER'S SLA CONTROL GRAPH AND ITS SPECIAL CASE INTERPRETATIONS

Type of Smart Contract	Entropy Measure (Uncertainty Index) of Ziply Fiber's SLA
Ziply Fiber's root SLA (Figure 4)	1.6094
Interpretation 1	0
Interpretation 2	0
Interpretation 3	0
Interpretation 4	0
Interpretation 5	0

TABLE II
ENTROPY MEASUREMENT OF CENTURYLINK'S SLA CONTROL GRAPH AND ITS SPECIAL CASE INTERPRETATIONS

Type of Smart Contract	Entropy Measure (Uncertainty Index) of CenturyLink's SLA
CenturyLink's root SLA (Figure 4)	1.3863
Interpretation 1	0
Interpretation 2	0
Interpretation 3	0
Interpretation 4	0

B. McCabe's Cyclomatic Complexity:

The Mccabe's Cyclomatic Complexity [20] is defined as:

$$C = N_e - N_n + 2 * N_{cc} \quad (2)$$

Where, C is the complexity, N_e is the number of edges of the control flow graph, N_n is the number of nodes of the control flow graph, and N_{cc} is the number of connected components.

TABLE III
COMPLEXITY MEASUREMENT OF ZIPLY FIBER'S SLA CONTROL GRAPH AND ITS SPECIAL CASE INTERPRETATIONS

Type of Smart Contract	Complexity Measure (Ambiguity Index) of Ziply Fiber's SLA
Ziply Fiber's root SLA (Figure 4)	3
Interpretation 1	1
Interpretation 2	1
Interpretation 3	1
Interpretation 4	1
Interpretation 5	1

TABLE IV
ENTROPY MEASUREMENT OF CENTURYLINK'S SLA CONTROL GRAPH AND ITS SPECIAL CASE INTERPRETATIONS

Type of Smart Contract	Complexity Measure (Ambiguity Index) of CenturyLink's SLA
CenturyLink's root SLA	2
Interpretation 1	1
Interpretation 2	1
Interpretation 3	1
Interpretation 4	1

Both entropy (uncertainty) and complexity (ambiguity) of Ziply Fiber's root SLA is higher compared to CenturyLink's SLA. From our observations and evaluations from Fig. 4, 5, 6, 7, 8, and 9 and Table I, II, III and IV, we found that in both vendors' SLAs, smart contract of Ziply Fiber was more ambiguous than smart contracts of CenturyLink.

VI. CHALLENGES, LIMITATIONS AND FUTURE WORK

One of the main challenges was to label all the tokens manually as ambiguous or non-ambiguous in the training dataset correctly. Labeling the dataset involved meticulous planning while preparing the dataset at the beginning of this project because many words are ambiguous literally for a lay-person but may not be considered as ambiguous by the lawyers who draft the SLAs.

Other challenge was to increase the accuracy of the existing model that we used to classify and detect the ambiguous words which were used to generate various interpretations of SLA that can later be translated into their respective smart contracts. Nevertheless, we are persistently working to gather more SLAs from vendors to increase our training dataset which will help increase the accuracy of the model.

Future work would be to use Bidirectional Encoder Representations from Transformers (BERT) to get much better and accurate predictions of the ambiguous words which is the state-of-the-art in Natural Language Processing and Machine Learning in recent times. In addition, study on formal frameworks to understand how the legal contracts are formalised is also significant. Also, comparing the ground truth of the smart contracts after their translation from traditional legal contracts with the lawyers and comparing the integrity of our ambiguity index with lawyer's measurement standard is a major work that we plan to finish very soon in the future.

VII. Conclusion

We introduced a novel idea on how we can study the ambiguous nature of legal contracts and Service Level Agreements (SLAs) of real vendors from the industry and how using smart contracts can help avoid the challenges of ambiguity in traditional legal contracts. Regardless of how popular a vendor is, their SLAs can still be vague, imprecise, and ambiguous that can put a customer into a myriad of confusion and difficulty. In this paper, we presented a fresh solution to an existing problem of ambiguity in legal contracts by gathering real-world SLAs of the top ISP vendors using a machine learning approach to train machine for detecting the ambiguous words in the legal contracts automatically. Since understanding an ambiguous legal contract is difficult and it can create several different interpretations for several different people, we studied all the interpretations and their behaviors thoroughly from the SLAs of two different ISP vendors. We derived and generated all possible interpretations from root SLA and then evaluated and compared different metrics which helped us to find the most ambiguous interpretation as well as the most ambiguous vendor's SLA as a whole. We were also able to validate our final conclusion and decide whether a given interpretation of an SLA was accurate or ambiguous by assessing the transaction fees and ambiguity index of all possible interpretations of the SLA. Moreover, we also compared two different SLAs and found which one is more ambiguous than the other. The main purpose of this paper is to study how the SLA contracts, even from the popular vendors, can create confusions and different interpretations in different customers by being ambiguous and how converting the traditional and ambiguous SLAs into smart contracts can help us find the right interpretation of a legal contract.

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