Discovering Power Laws in Entity Length

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Abstract

This paper presents a discovery that the length of the entities in various datasets follows a family of scale-free power law distributions. The concept of entity here broadly includes the named entity, entity mention, time expression, aspect term, and domain-specific entity that are well investigated in natural language processing and related areas. The entity length denotes the number of words in an entity. The power law distributions in entity length possess the scale-free property and have well-defined means and finite variances. We explain the phenomenon of power laws in entity length by the principle of least effort in communication and the preferential mechanism.

1 Introduction

The rank-frequency of words in natural language follows a family of power law distributions; such distributions are known as Zipf’s law (Zipf, 1936, 1949). Zipf’s law has been receiving tremendous attentions in statistical/quantitative linguistics for more than 70 years (Zipf, 1936, 1949; Parker-Rhodes and Joyce, 1956; Simon, 1955, 1960; Mandelbrot, 1953, 1961; Carroll, 1967; Chen, 1991; Li, 1992, 2002; Corominas-Murtra and Solé, 2010; Piantadosi, 2014). While these research narrow the power law distributions in the words’ rank-frequency, we discover that the power law distributions also appear in another form of natural language: entity length.

The concept of entity in this paper broadly includes the named entity (Grishman and Sundheim, 1996; Chinchor, 1997; Sang and Meulder, 2003), entity mention (including anchor text) (Pradhan et al., 2013; Ling and Weld, 2012), time expression (Pustejovsky et al., 2003a,b), aspect term (Liu, 2012; Pontiki et al., 2014), and domain-specific entity (Fukuda et al., 1998; Takeuchi and Collier, 2005) that are well investigated in various areas related to natural language processing. The entity length is defined by the number of words in an entity. Table 1 shows some examples of the entities and their length.

| Entity | Length |
|--------|--------|
| 46,480 | 1      |
| tRNAGln| 1      |
| Chinese| 1      |
| Walter Cristofolotto| 2 |
| United Arab Emirates| 3 |
| March 16, 2005| 4 |
| 10:00 p.m. on August 20, 1940| 7 |
| human cytomegalovirus (HCMV) major immediate| 7 |
2 Related Works

Our work is related to Zipf’s law and the distributions of word length and sentence length.¹

2.1 Zipf’s Law

Zipf’s law (Zipf, 1936, 1949) reveals that the \(r\)-th most frequently occurring word in a corpus has the frequency \(f(r)\) that is proportional to

\[
f(r) \propto r^{-z}
\]

where \(r\) denotes the frequency rank of a word and \(f(r)\) denotes its frequency; the exponent \(z\) is observed to be very close to 1. The Zipf’s law has been observed universally in many languages (Zipf, 1949; Li, 2002; Corominas-Murtra and Solé, 2010; Piantadosi, 2014)

2.2 Word Length and Sentence Length

According to the review by Grotjahn and Altmann (1993), Fucks (1955, 1956) first demonstrated that the word length in a corpus empirically and theoretically follows a variant of Poisson distributions. The word length of a natural corpus has been observed to follow the variants of Poisson distributions in more than 32 languages (Best, 1996). Williams (1940) and Wake (1957) observed that the sentence length can be fitted by a family of lognormal distributions. Sigurd et al. (2004) observed that word length and sentence length from English, Swedish, and German corpora can be fitted by a variant of gamma distributions.

2.3 Connections to Related Works

Like words and sentences, entities also play a critical role in our communicative system. Word frequency and word/sentence length have attracted the interest from various researchers like linguists and statisticians. We wish that the entity length distributions could also provide some insights together with words and sentences for the understanding of our communicative system.

3 Power Laws in Entity Length

3.1 Datasets

We use nine datasets that are developed for entity analysis and one derived dataset to analyze the length distributions of the entities.² Following we briefly describe the datasets.

Table 2: Examples of strange entities in ACE04

| (1) the Taliban regime, which now controls over 80% of land in the country but is so far only recognized by Pakistan, Saudi Arabia and the United Arab Emirates |
| (2) Kuwaiti team, which he led to win the Gulf Cup on two occasions and take fourth place in the last Asian Nations Championship in the Emirates, as well as second place in the Asian Games in Bangkok in 1998 |

BBN (Weischedel and Brunstein, 2005) consists of Wall Street Journal articles for pronoun coreference and entity analysis. We concern the entities.

ACE04 (Doddington et al., 2004) consists of various types of data for entities and relations in three languages (i.e., Arabic, Chinses, and English). We only consider the entities in English.

ACE04*. We find that quite a few entities in the ACE04 dataset are different from the formal entities and should be pruned to several entities. Table 2 shows two examples of such strange entities. We apply the Stanford Tagger (a stats-of-the-art tagger) (Finkel et al., 2005) to all the ACE04’s entities to prune the entities for analysis. The pruned entities are denoted by ACE04*.

CoNLL03 (Sang and Meulder, 2003) is a benchmark dataset derived from Reuters RCV1 corpus, with 1,393 news articles between August 1996 and August 1997. It contains 4 types of named entities.

OntoNotes5 (Pradhan et al., 2013) is a large dataset collected from different sources over a long period for the analysis of named entities and entity mentions. It contains 18 types of entities.

Twitter includes two corpora: WNUT16 (Strauss et al., 2016) and Broad Twitter Corpus (Derczynski et al., 2016). Both of the corpora are collected from Twitter for named entity analysis.

ABSA14 (Pontiki et al., 2014) is the benchmark dataset for the SemEval-2014 aspect-based sentiment analysis. We concern the aspect terms.

TimeExp consists of three corpora that are developed for time expression analysis: TempEval-3 (including TimeBank (Pustejovsky et al., 2003b), Gigaword (Parker et al., 2011), AQUAINT, and Platinum corpus (UzZaman et al., 2013)), WikiWars (Mazur and Dale, 2010), and Tweets (Zhong et al., 2017; Zhong and Cambria, 2018).

Wikipedia (Ling and Weld, 2012) treats the anchor text (i.e., the text in the hyperlinks) from Wikipedia (20110513 version) as entity mentions.
| Dataset       | #Entities | Average Length |
|--------------|-----------|----------------|
| BBN          | 98,477    | 1.26           |
| ACE04        | 29,949    | 2.43           |
| ACE04*       | 20,462    | 1.30           |
| CoNLL03      | 35,087    | 1.45           |
| OntoNotes5   | 155,413   | 1.85           |
| Twitter      | 20,515    | 1.39           |
| ABSA14       | 7,839     | 1.46           |
| TimeExp      | 18,484    | 1.80           |
| Wikipedia    | 2,690,849 | 2.10           |
| Bioinformatics | 450,729  | 1.80           |

**Bioinformatics** consists of fourteen corpora developed for biological/biomedical entity analysis: AnatEM (Pyysalo and Ananiadou, 2014), BC2GM (Smith et al., 2008), BC5CDR (Wei et al., 2015), BioNLP09 (Kim et al., 2008), BioNLP11 (Pyysalo et al., 2012), BioNLP13CG (Pyysalo et al., 2015), BioNLP13GE (Kim et al., 2013), BioNLP13PC (Ohta et al., 2013), CHEMDNER (Krallinger et al., 2015), CRAFT (Bada et al., 2012), ExPTM (Pyysalo et al., 2011), JNLPBA (Kim et al., 2004), LINNAEUS (Gerner et al., 2010), NCBI-Disease (Dogan et al., 2014).

Table 3 summarizes the total number of the entities and the average entity length in the datasets. For each of the datasets that include several corpora (i.e., Twitter, TimeExp, and Bioinformatics), we simply merge the whole entities from all the corpora for analysis. Except ACE04 and Wikipedia, the average length of the entities is less than 2 (words). For ACE04, the average length of its pruned entities (i.e., ACE04*) is less than 2. For Wikipedia, the entities are the anchor text, which could be as long as the sentences.

### 3.2 Distributions of Entity Length

Although these datasets differ from each other in terms of source, domain, text genre, generated time, corpus size, entity type, and annotation criterion, the length of their entities follows a similar distribution. Figure 1 plots the distributions of the entity length in a log-log scale. We can see that the entity length can be fitted by a family of power law distributions, defined by equation (2), with the scale-free property (Barabási and Albert, 1999).

\[
p(l) = Kl^{-\alpha} \tag{2}\]

where \(l\) denotes the length of the entities and \(p(l)\) denotes the percentage of the \(l\)-length entities over the whole entities; the constant \(K\) is unimportant and the exponent \(\alpha\) is of interest.

Figure 1 shows that the power laws fit BBN’s entity length distribution with \(\alpha = 4.58\), fit ACE04’s with \(\alpha = 2.77\), fit ACE04*’s with \(\alpha = 3.59\), fit CoNLL03’s with \(\alpha = 4.26\), fit OntoNotes5’s with \(\alpha = 4.34\), fit Twitter’s with \(\alpha = 3.85\), fit ABSA14’s with \(\alpha = 3.33\), fit TimeExp’s with \(\alpha = 3.62\), fit Wikipedia’s with \(\alpha = 3.44\), and fit Bioinformatics’s with \(\alpha = 3.10\).

Except in ACE04, all the \(\alpha\) are greater than 3, indicating that these power law distributions have well-defined means and finite variances (Newman, 2005). For ACE04, after its entities are pruned to formal entities (i.e., ACE04*), the \(\alpha\) is also greater than 3. That means under formal entities, all the power laws have defined means and variances.

### 3.3 Explanation

The phenomenon of power laws in entity length can be explained by the principle of least effort in communication (Zipf, 1949) and the preferential mechanism (Barabási and Albert, 1999). That is, whenever we need an entity to express our idea, on premise of being able to make our idea understood, we would prefer to use a short one; short entity can reduce both the speaker and listener’s effort. For example, to express the country of China, most of us should prefer to use ‘China’ rather than “People’s Republic of China”; similarly, most of us should prefer ‘America’ or ‘United States’ than ‘United States of America.’ In this sense, the distribution of entity length indicates the probability of the number of words we prefer to use in entities. The preference for short entities leads the power law distributions to possess the scale-free property, similar to the preferential mechanism in random network (Barabási and Albert, 1999).

## 4 Conclusion

We discover that the entity length follows a family of scale-free power law distributions, with defined means and finite variances. We wish the discovery could provide a consideration for the understanding of how we humans use language. The discovery also generates some open questions; for example, given that entity length follows the power law distributions and word/sentence length follows the Poisson distributions (Fucks, 1955, 1956), lognormal distributions (Williams, 1940; Wake, 1957), or gamma distributions (Sigurd et al., 2004), how much information we need to fill in the gaps among the words, entities, and sentences?
Figure 1: Scale-free power law distributions in entity length. (a) BBN ($\alpha = 4.58$), (b) ACE04 ($\alpha = 2.77$) and ACE04* ($\alpha = 3.59$), (c) CoNLL03 ($\alpha = 4.26$), (d) OntoNotes5 ($\alpha = 4.34$), (e) Twitter ($\alpha = 3.85$), (f) ABSA14 ($\alpha = 3.33$), (g) TimeExp ($\alpha = 3.62$), (h) Wikipedia ($\alpha = 3.44$), (i) Bioinformatics ($\alpha = 3.10$). Except in ACE04, all the $\alpha$ are greater than 3, indicating that those power law distributions have well-defined means and finite variances.
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