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Tranzzl!n9o: A Human Computation Approach to English Translation of Internet Lingo

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Abstract

Lingo is an emerging language on the Internet. Providing a standardized definition remains difficult due to continuous changes made to its nature. We proposed Tranzzl!n9o, a crossword puzzle game for engaging crowds to translate Internet lingo. Players provide explanations for lingo in parallel and iteratively verify the explanations from other players. Crowd-sourced translations are very informative containing explanations as well as lingo usage.

Introduction

We are studying English translation of Internet lingo. Lingo is not formalized in linguistics. It contributes to language barriers between different cultures, generations and groups as well as out-of-vocabulary (OOV) issues in the language process. Understanding the meaning of lingo can assist in the analysis of web content and various cultures in online communities.

In previous work, most research used machine computation to perform text normalization with human participants rarely involved. In the machine translation approach, Aw et al. (2006) proposed a statistical model considering lingo as a foreign language to English. In the speech recognition approach, researchers (2008) view SMS messages as an alphabetic approximation of a phonetic form depending on manually encoded letter-to-phone rules and dictionaries.

However, the user-created and time-evolved nature of Internet lingo is difficult to describe simply by static rules and predefined dictionaries. Translation is more related to understanding the context in a sentence. In general, humans are sophisticated enough to capture contextualized meaning.

We collected the opinions from crowds rather than hiring individuals to translate lingo, as these translations may contain biases. A game design could provide good incentives to engage crowds. Our goal is to construct an Internet lingo dictionary with human knowledge in an enjoyable and creative way. We proposed Tranzzl!n9o mapped from a well-known crossword puzzle game. Our game performs parallel and iterative human computation via *Unlingofy* and *Lingofy* tasks.

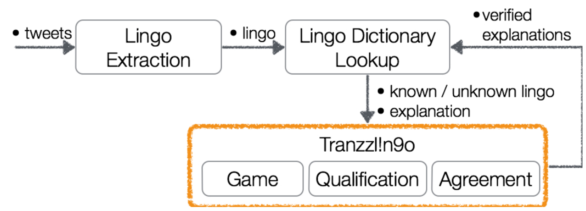
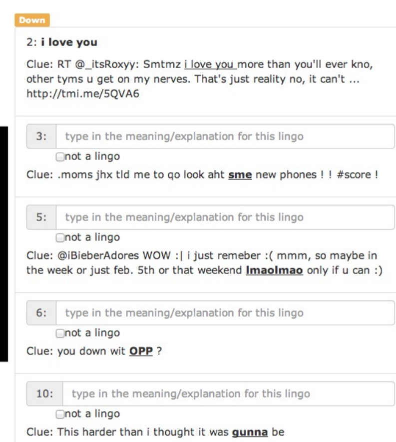


Figure 1: System framework

Tranzzl!n9o System

We use tweets in Tweets2011 corpus from TREC as our lingo source data. For preprocessing, we extract lingo from the given tweets using rule-based filters similar to previous work (2011) and removing proper nouns using a POS tagger published by Owoputi et al. (2013). We lookup explanations for lingo in our lingo dictionary initialized with the database from NoSlang.com[1]. If an explanation exists in the dictionary, the lingo is labeled "known lingo", with unknown lingo aptly labeled "unknown lingo". The preprocessing results are used to generate the puzzles in Tranzzl!n9o. (Figure 1)

(a) Puzzle



(b) Clue area

Figure 2: Trazzl!n9o: "translate"+"puzzle"+"lingo"

[1]http://www.noslang.com/dictionary

Game Instead of formal words in traditional crossword puzzles, we play with lingo. Our design idea is that the meaning of lingo within a sentence depends on the context. If we translate the lingo in only a literal sense, it may lose meaning. Thus, a sentence with lingo can be used as a clue to help humans understand the meaning of the lingo.

There are two tasks performed in our game: *Lingofy*, typing lingo into a puzzle (Figure 2a) from an English description or a clue (Figure 2b), and *Unlingofy*, which involves translating lingo (Figure 2a) into plain English (Figure 2b). Note that if the target word is not a lingo, players can report it by selecting the check-box "not a lingo".

Unlingofy is generated by unknown lingoes written in puzzles and their tweet sentences in clue area. *Lingofy* is generated by known lingoes blanked out in puzzles and their corresponding explanations in clue area. We can generate puzzles with different ratios of *Unlingofy* and *Lingofy* task to adjust the collection rate of new explanations and verification of existing explanations.

During the game process, players are given obvious hints via sentence clues and hidden hints via word cross-correlation in the puzzle. The hidden hints are especially helpful when some of the explanations are difficult to associate with the target lingo since the lingo is free and creative. The crossed situations could be considered constraints as well as hints to the guessing of lingo.

Qualification We have ground truth seeding questions in puzzles. In our experiments, we have 9 to 11 questions in one game round. We make the seeding questions in *Lingofy*. A player should answer over 1/2 of all questions and get correct answers in over 1/3 of seeding questions to be qualified.

Agreement A two-stage agreement allows for collaboration between players. Players contribute to both translation and verification agreements in one game round by completing *Unlingofy* and *Lingofy* task.

First, the translation agreement associates with parallel human computation in *Unlingofy*. The explanations from different players are aggregated if their meanings are similar. Note that an annotator is used for aggregation. Second, the verification agreement associates with iterative human computation in *Lingofy*. The explanations collected from *Unlingofy* will be verified by other players in *Lingofy*. In other words, if a player answers the correct lingo by looking at the explanation, the explanation is verified by this player.

Preliminary Experiments

We chose MTurk, a popular and feasible platform to run our experiments. There were 61 players, with 45 players qualified by our qualifications. The observations supported that humans take context into consideration (Table 1). The second explanation explains why the writer used specific lingo. The third explanation explains the context of the sentence and is very different from the original word "kill".

In the *Lingofy* task, there were 209 questions asked to all 61 players. Among 209 questions, 110 questions were correctly verified, so the correctness ratio was 52.63% (110/209). If we consider the 45 qualified players, the correctness ratio rose to 68.83% (106/154).

Lingo	"Killl"
Tweet sentence	Killl it! RT @username0983 @username9432 ur team going home today gooooo #jets lol
Explanation	1. murder 2. extra emphasis 3. You're doing great. Masterful job.

Table 1: Collected explanations from players

In the *Unlingofy task*, we evaluated the 138 explanations reported from 45 qualified players. Among the 138 explanations, 101 explanations were correct, so the correctness ratio was 73.19%. If we consider the aggregated explanations that passed the translation agreement, there were 54 explanations agreed upon by at least two players. Among 54 explanations, 49 explanations were correct. The correctness ratio is 90.74% in the aggregation case.

Conclusions and Future Work

Tranzzl!n9o maps the translation tasks to a well-known crossword puzzle game and performs parallel and iterative human computation. Our game allows humans to translate lingo considering the context of a sentence. Crowd-sourced translations are very informative containing not only explanations but also lingo usage. Our next step is to engage crowds with more game elements and analyze the performance of parallel and iterative human computation. Keeping our lingo dictionary updated, we hope to support OOV issues, an annotated corpus of lingo for machine learning and help Internet users better-understand lingo.

Acknowledgement

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