Improving Accuracy of Named Entity Recognition on Social Media Data

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Contribution

We present a system for improving the accuracy of one NLP technique, Named Entity Recognition or NER, on Twitter data by training a recognizer specifically for this type of data. This training data is obtained from the Amazon Mechanical Turk crowdsourcing platform.

Data

Our experiments were conducted on data collected by a third party between March 2007 and November 2008. It consists of approximately 150 million status updates from 1.5 million users, which are stored in a database and indexed with Lucene.

Named Entity Recognition

Named Entity Recognition (NER) is the process of finding those words in a body of text that refer to entities: people, places, products, events, or organizations. We will investigate finetuning a modern technique for this task, Conditional Random Fields, to better suit Twitter data.

Twitter

Twitter is a platform for users to post short messages ("status updates" or "statuses"). These messages are often informal, leading to poor grammar, punctuation, and capitalization. These special features lead to poor performance from traditional NER systems. Other features of the Twitter platform that set it apart from other types of text include the conventions that have accumulated around it:

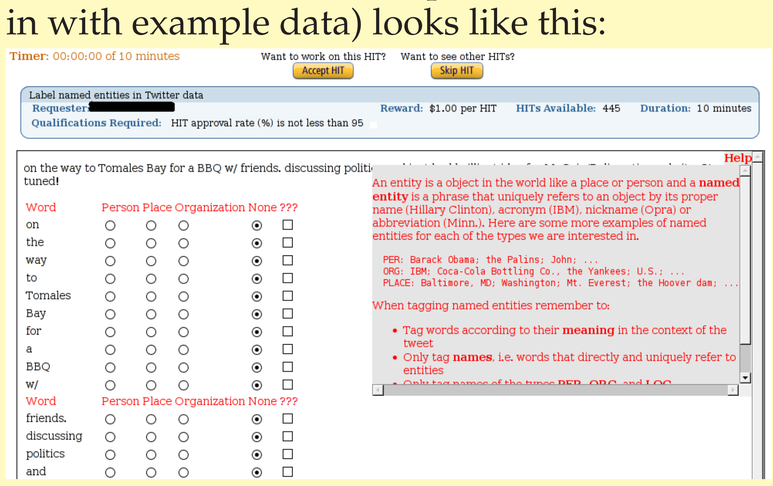
- Hashtags are words or abbreviations prefaced with a "#" character, which are used either as metadata or as a word.
- User mentions consist of a username prceded by an @ character, and can be used to name a person or direct a tweet at them.
- Retweets are designated by the characters "RT", followed by a username and the text of a tweet that user posted.
- URLs are also often present in tweets, using the familiar `http://` notation, but often use an external URL shortener like `bit.ly` or `is.gd` to fit better within the 140 character limit of Twitter.

We can take advantage of these conventions to do a better job recognizing words that may refer to entities. For example, hash tags are often used when people tweet from events, mentioning the event by a hashtag.

Mechanical Turk

Amazon Mechanical Turk (MTurk) is a system which allows people ("requesters") who need simple tasks done by humans to find other people ("workers") to do those tasks. We used this system to generate training data for our machine learning algorithm which will accomplish the end goal.

Using Mechanical Turk is as simple as defining Human Intelligence Tasks ("HITs") which are basically a template for the webpage that workers will eventually interact with, and providing a spreadsheet with a list of values that should be fill this template. Our HIT (filled in with example data) looks like this:



We had a total of 270 workers, who completed 3,080 HITs. Each HIT was composed of five tweets: one which had been previously annotated by us ("Gold"), and four which had not been annotated. Each HIT was given to two different workers, in order to build better consensus.

Finding Agreement

Annotating our data with MTurk was cheap, but there are difficulties resulting from the informal nature of the annotators and potential for disagreement between them. There is also the consideration that unethical workers may use robots to fill out the form, resulting in completely invalid answers. To address this problem, we developed an algorithm based on Google's PageRank which determines inter-worker agreement. Pseudocode is shown below.

WORKER-AGREE : $results \rightarrow scores$

1 $worker\_ids \leftarrow$ ENUMERATE(KEYS($results$))
  ▷ Initialize A
2 $A[worker1, worker2]$
  $\leftarrow$ SIMILARITY($results[worker1]$, $results[worker2]$)
  ▷ Normalize columns of A so that they sum to 1
  ▷ Initialize x to be normal: each worker is initially trusted equally.
3 $x \leftarrow \left\langle \frac{1}{\sqrt{n}}, \ldots, \frac{1}{\sqrt{n}} \right\rangle$
  ▷ Find the largest eigenvector of A, which corresponds to the agreement-with-group value for each worker.
4 $i \leftarrow 0$
5 **while** $i < max\_iter$
6 **do** $x_{\text{new}} \leftarrow$ NORMALIZE($A \times x$)
7 $diff \leftarrow x_{\text{new}} - x$
8 $x = x_{\text{new}}$
9 **if** $diff < tolerance$ **break**
10 $i \leftarrow i + 1$
11 **return** x

Informally, this score has been observed to correlate well with annotation quality.

Training a NER system

We investigated two NER systems: the Stanford Named Entity Recognizer (`http://nlp.stanford.edu/software/CRF-NER.shtml`) and the Mallet Sequence Tagger (`http://mallet.cs.umass.edu/sequences.php`). Both systems have advantages, and both will be investigated in parallel in the future.

- The Stanford NER has the advantage of including good feature extractors, which can allow the NER system to properly tag words it has never seen before, based on features like sentence structure.
- Mallet has the advantage of easy-to-access online Javadoc, which make it easy to write a program which does NER rather than simply use the simple (and often insufficient) demonstration program included.

Results

Amazon Mechanical Turk proved an effective and inexpensive method of gathering training data for our machine learning algorithm. Using a purpose-designed algorithm, we can take raw data from MTurk and produce high-quality training data in a reasonable amount of time.

Future Work

In the future we hope to train NER systems on many chosen subsets of the AMT data, in order to judge the impact that a single exceptionally good or bad worker can have on accuracy of the trained NER system.

With this data, we hope to compare the similarity metric we have established to the individual worker's efficacy, in order to formally establish its usefulness as a worker quality metric.

Open Questions

- Could an online version (i.e., one that takes new incremental data over time) of the MTurk agreement algorithm allow for real-time spammer detection? This would allow better use of time, since when a spammer is detected they can be disallowed from completing more HITs, letting other legitimate workers do the HITs instead, so that fewer HITs need to be resubmitted.
- How many annotations are necessary to train a good NER system? How can we detect this condition with a machine learning algorithm?
- If we can build a system that automatically trains itself: Could a NER system bootstrap itself via AMT? The system could take a large arbitrary corpus and automatically submit jobs to AMT, then train itself based on those results.