



Crowdsourcing for NLP

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What is crowdsourcing?

- ♦ **How many of you have done crowdsourcing?**
 - Mechanical Turk
 - Other?



Many uses of crowdsourcing

◆ Outsourcing

- Research, design, writing, coding, ...
 - Kaggle, Innocentive, Guru, oDesk, eLance
 - Wikipedia, Foldit ...

◆ Find crowd wisdom

- Prediction markets, product ratings, news selection

◆ Social science research

- Online experiments: e.g. sensitivity to pay
- Surveys: personality, politics, preferences,

◆ Obtain labels

- Images, speech, videos ...
- Text

Today: NLP microtasks





Ready to launch?

Hire

Work

The #1 Resource for Small Business & Entrepreneurs

TRANSLATION AS A SERVICE

Human corrected machine translation service that enables businesses to communicate globally.

TRY IT FOR FREE

SIGN UP

*no credit card needed



6,951 editors

2,849,184 words translated

6 languages

Stop spam, read books

- ◆ **Digitizing NYTimes archives, books**
 - The parts where OCR fails.
- ◆ **750,000,000 “volunteers”**
 - 100 million CAPTCHAs per day

following finding

Microtasks: Mechanical Turk

Task type	Estimated Proportion
Web scouring	42%
Images related	22%
Text related & OCR	17%
Audio related	14%
Video related	3%
Testing / Quality Assurance	3%

Ipeirotis



Webscouring

- ◆ Verify a restaurant listing
- ◆ Match my products to Amazon products
- ◆ Find official websites for places, companies, ...
- ◆ Find the email addresses for wedding venues
- ◆ Find the school website and its school supply list
- ◆ Find Yelp reviews for businesses
- ◆ Categorize a Twitter search query
- ◆ Find a company name from an email domain
- ◆ Find main title, subtitle, and authors for a book
- ◆ Categorize web pages



First big NLP use: 2008

Cheap and Fast — But is it Good? Evaluating Non-Expert Annotations for Natural Language Tasks

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Abstract

Human linguistic annotation is crucial for many natural language processing tasks but can be expensive and time-consuming. We explore the use of Amazon's Mechanical Turk system, a significantly cheaper and faster method for collecting annotations from a broad base of paid non-expert contributors over the Web. We investigate five tasks: affect recognition, word similarity, recognizing textual entailment, event temporal ordering

and financial cost. Since the performance of many natural language processing tasks is limited by the amount and quality of data available to them (Banko and Brill, 2001), one promising alternative for some tasks is the collection of non-expert annotations.

In this work we explore the use of Amazon Mechanical Turk¹ (AMT) to determine whether non-expert labelers can provide reliable natural language

EMNLP



Snow, O'Connor, Jurafsky & Ng

- ◆ **Affect Recognition**

$\text{fear}(\text{"Tropical storm threatens NYC"}) > \text{fear}(\text{"Awesome goal for Beckham"})$

- ◆ **Word Similarity**

$\text{sim}(\text{man}, \text{boy}) > \text{sim}(\text{man}, \text{rooster})$

- ◆ **Textual Entailment**

if "Microsoft was established in Italy in 1985" then "Microsoft was established in 1985"?

- ◆ **Word Sense**

"the West Bank" v. "the Bank of America"

- ◆ **Temporal Annotation**

denoted happens before collapsed in:
"The condemned building collapsed when the



Image annotations: 2010

Collecting Image Annotations Using Amazon's Mechanical Turk

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Abstract

Crowd-sourcing approaches such as Amazon's Mechanical Turk (MTurk) make it possible to annotate or collect large amounts of linguistic data at a relatively low cost and high speed. However, MTurk offers only limited

can predict not just the presence and location of certain objects in an image, but also the relations between objects, their attributes, or the actions and events they participate in. Such information can neither be obtained from standard computer vision data sets such as the COREL collection nor from



ImageNet

IMGENET

14,197,122 images, 21841 synsets indexed

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ImageNet is an image database organized according to the **WordNet** hierarchy (currently only the nouns), in which each node of the hierarchy is depicted by hundreds and thousands of images. Currently we have an average of over five hundred images per node. We hope ImageNet will become a useful resource for researchers, educators, students and all of you who share our passion for pictures.

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an image database organized according to the **WordNet** hierarchy

NLP uses of M-turk

- ◆ Translation
- ◆ Summarization
- ◆ Information Extraction
- ◆ Document relevance
- ◆ Word-sense disambiguation
- ◆ Figure captions
- ◆ Labeling sentiment, intent, style...
- ◆ Getting user information and associated text

Anything in NLP
- generating data or labels
- assessing quality



Schedule

- ◆ Taxonomy of crowdsourcing and human computation
- ◆ The Mechanical Turk crowdsourcing platform
 - How to set up and run an experiment
- ◆ **Break**
- ◆ Quality control (and Statistical analysis?)
- ◆ Limits of Mechanical Turking (and Ethics?)
- ◆ Case Studies in NLP
 - Machine translation
 - Information extraction
 - Word sense disambiguation
 - Computational social science
- ◆ Wrap-up

