WordSleuth:

Deducing Social Connotations from Syntactic Clues

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Plan

I. Research Question

II. WordSleuth

  A. Game-play

  B. Taboo list

III. Machine Learning

  A. Data representation

  B. Classification Algorithms

IV. Future Possibilities

V. Question and Answer

I. Question

Can humans derive complex social ideas from simple text?

- intention: deception, persuasion
- attitude: formality, politeness, rudeness
- emotion: embarrassment, confidence

57%-71% (Pearl and Steyvers 2010)

...Can computers?

Example

Social connotations include:

confidence	deception
disbelief	embarrassment
persuading	politeness
rudeness	formality

Example Text Input:

“I don't care if Nancy laughs at my outfit – I think I look good!”

II. WordSleuth

Problem: Where to get the data?

Solution: Create WordSleuth, a Game-With-A-Purpose (GWAP) to encourage people to annotate data.

GWAP: Game created specifically to obtain data related to a particular research area.

(von Ahn 2006)

II. WordSleuth: My Role

To make improvements to the game:

A. Enable online functionality

B. Taboo-list functionality

Result II. A: Online Game App

www.gwap.ss.uci.edu

Word Sleuth

Test your social language intelligence

The message was: You know that the new findings at the symposium prove my theory and I can list at least 20 papers to disprove you before you even finish reading the titles.

You guessed: confidence
The answer: persuading

Play more!

II. A. The Online Game Application

Completing the web application of the game

- Currently **2,185** Annotated Messages with **8,941** annotations,
- Up from **1,167** Annotated Messages with **3,198** annotations
- → **187%** increase in messages, **280%** increase in annotations

II. B. Online Game App

Are people any good at it? Yes!

target ↓ / guesses →	confidence	deception	disbelief	embarrassment	formality	persuading	politeness	rudeness
confidence	**84.4**	2.0	2.0	0.8	1.0	6.1	2.3	1.3
deception	4.5	**74.3**	4.3	2.4	1.1	7.8	3.2	2.4
disbelief	2.7	4.1	**80.7**	3.3	1.3	1.9	2.7	3.3
embarrassment	0.4	3.0	5.6	**83.0**	2.1	1.1	2.7	2.1
formality	1.4	0.0	0.7	1.0	**70.5**	2.4	22.4	1.7
persuading	6.1	5.1	0.8	0.6	3.0	**80.2**	3.0	1.2
politeness	1.6	2.2	0.6	1.8	13.8	3.4	**75.4**	1.2
rudeness	2.1	1.2	3.1	1.9	1.6	2.9	1.0	**86.1**

Baseline: 1/8 = 12.5%

Average: 80.4%

II. B. Taboo List

Log Out | Play the Game | Instructions | Top Scores | Contact

Word Sleuth

Test your social language intelligence

Current score for shamu
Expressive: 0 Receptive: 8505 E-IQ: N/A R-IQ: 118 Activity Points: 447

You are playing on medium difficulty. You will earn 2x the base number of points.

Express this:
persuading

Don't use any of these taboo words:
persuade, persuading, persuasion, persuades, persuaded, opening, learned, million

My message is complete!

II. B. Taboo List

- By discouraging use of words already well-represented in the data, we encourage breadth and variety of data.

- Makes the game a bit more challenging for players.

- Makes the job of the classifier algorithms harder, as unigrams will have less direct correlation with class.

II. B. Taboo List

- “Taboo Words” calculated using Mutual Information
- Mutual Information: A measure of correlation

Example:

If category “confidence” has 10 instances of “Nancy”, and no other category does, the mutual information will be high

If all categories have the same number of a common word (such as “the”) the mutual information will be low.

Results II. B: Taboo List

> **rudeness**: popped, unprofessional, spotty

> **disbelief**: jumped, megaphone, twenty

> **persuading**: fast, alcohol, pay

> **deception**: still, blonde, reality

> **embarrassment**: accidentally, deodorant, surprising

> **formality**: abuse, calm, soldier

> **politeness**: yelled, scores, nices

> **confidence**: nancy, modest, respectable

III. Machine Learning: A. Data Representation

How to make use of the data? We can't just feed strings of English directly to the learning algorithms.

Message ID : MessageText : Target Cue: Creator : Guesses/Category

```
1049 This is a very nice house you have here, Mrs.
  Smith, and such good coffee.   formality
  labsubjectcl0 1  1  0  0  0  0  4  0  0  0
```

III. Machine Learning
A. Data Representation

So what features do we use anyway?

Originally:

- Vocabulary (that appears more than once in the data)

- Bigrams/Trigrams (word sequences)

- punctuation count

- types:tokens ratio (unique words : total words)

Added:

- interrobangs ?!

- ! : ? ratio

- sub clause analysis

...Over **4000** features and counting!

III. Machine Learning:
A. Data Representation

Solution: Feature Extraction

Represent data as a list of ordered triples with a category

(MessageID : FeatureID : Feature Value) → Target Cue

Sparsity: Allows us to ignore features not present for a given example.

III. Machine Learning

What do we do with all that data anyway?

Detective Data

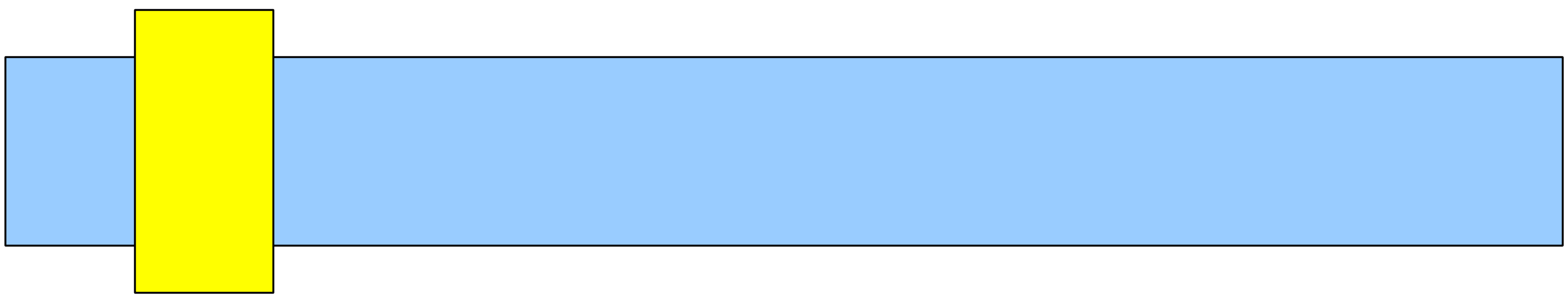
III. Machine Learning
B. Classification Algorithms

- Previously used: SMLR (Sparse Multinomial Logistic Regression): 59% (Pearl and Steyvers 2010)
- KNN (K Nearest Neighbors)
- Transductive Clustering

III. Machine Learning
B. Classification Algorithms

10-fold-cross-validation:

- Train/Transduce algorithm on 90% of the data, test it on 10%



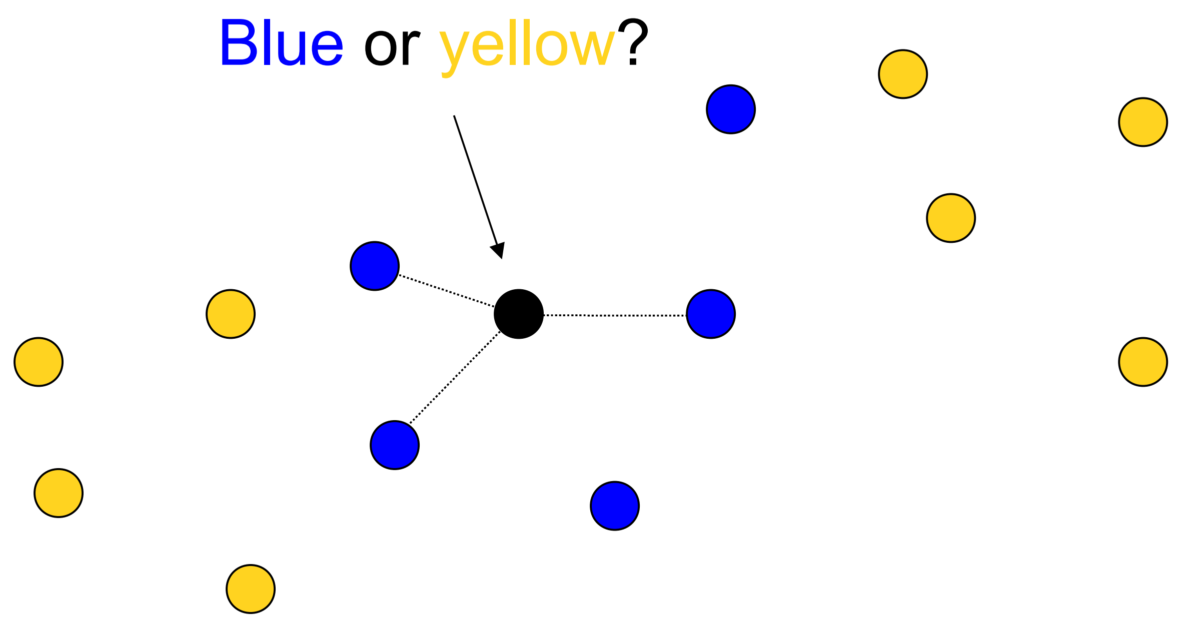
Base line for Machine Learners: 13.5%

(most common category)

III. Machine Learning
B. Classification Algorithms

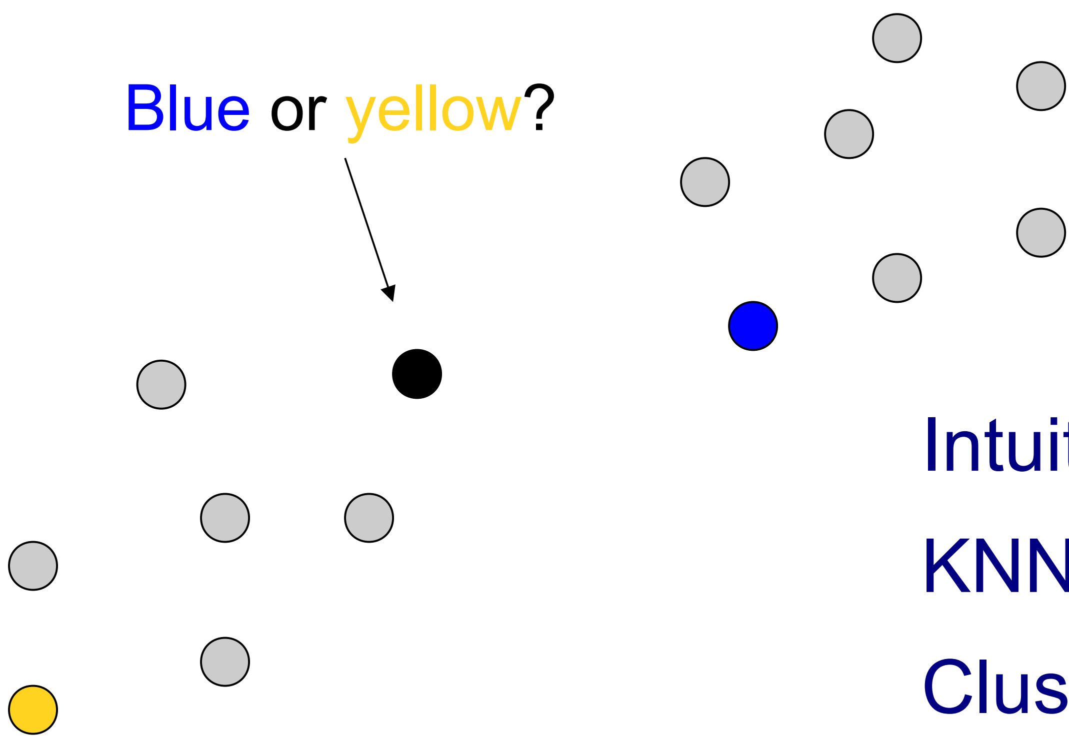
KNN – K nearest neighbors:

Preliminary Success: **75.7%** test accuracy



III. Machine Learning
B. Classification Algorithms

Transductive Clustering vs KNN



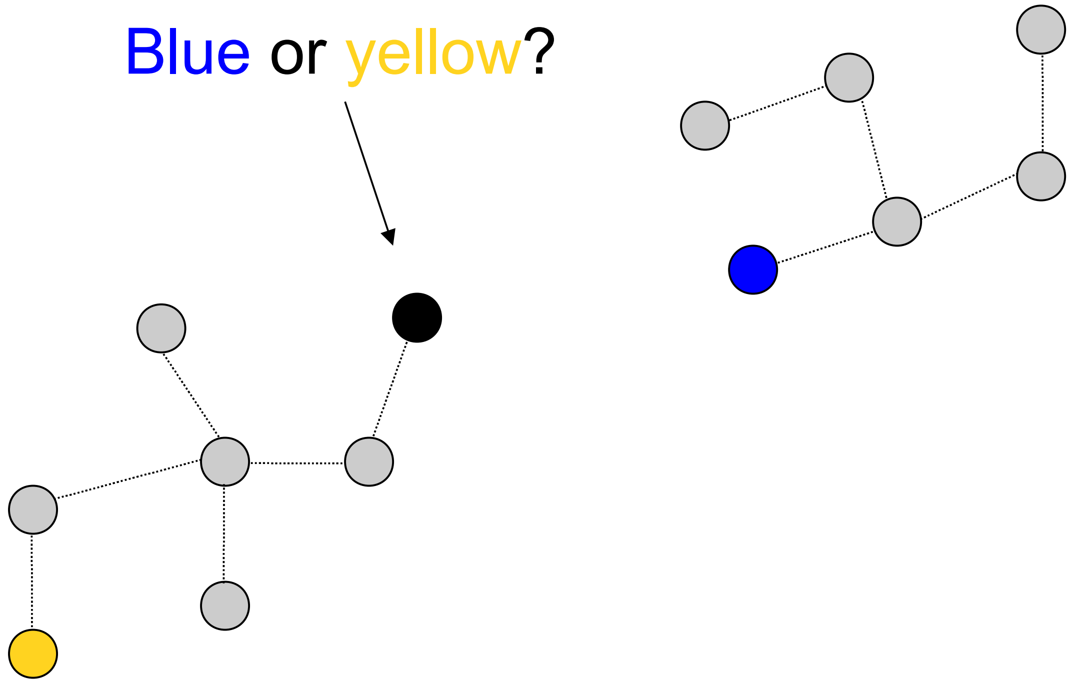
Intuition: ?

KNN: blue

Clustering: yellow

III. Machine Learning
B. Classification Algorithms

Transductive Agglomerative Clustering



III. B. Agglomerative Clustering

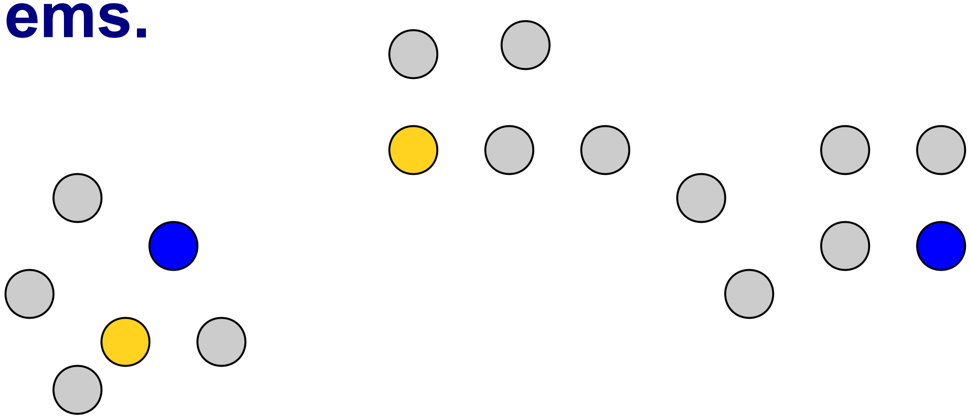
Mean accuracy: 12.99% (deviation 0.00618)

… remember, baseline is 13.5%

Why so poor?

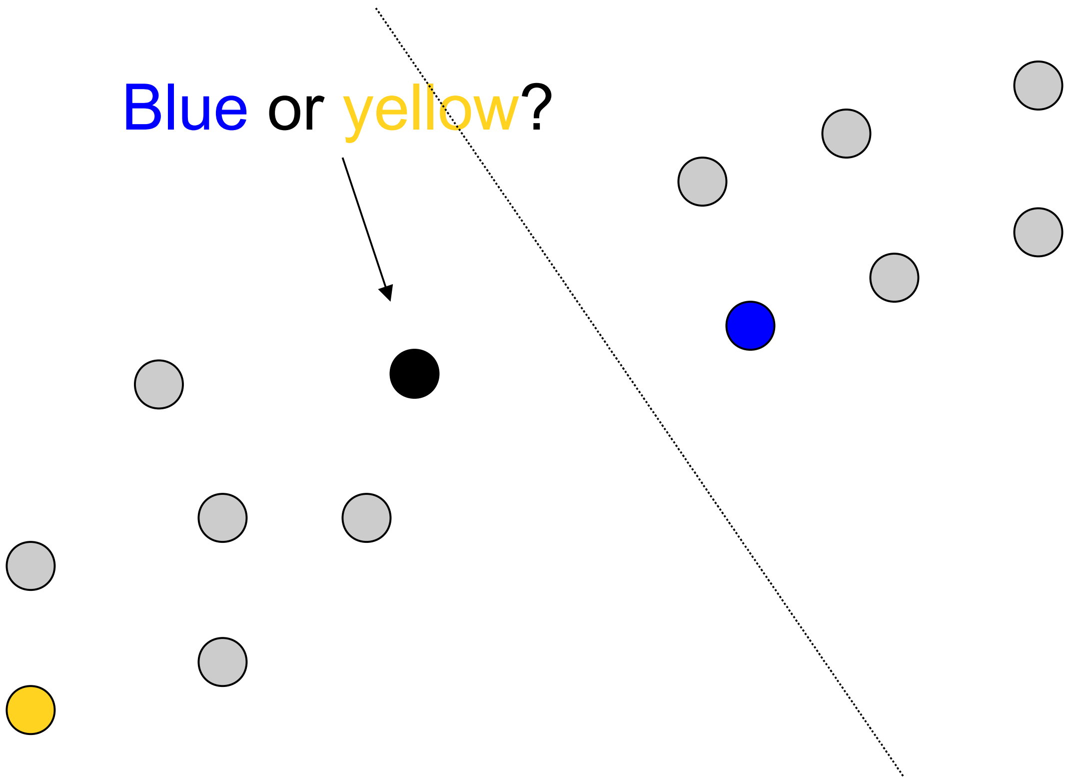
"Unlabeled patterns take the label of the cluster with which they are joined. *It never joins clusters with different labels.*"

Thus, very near clusters and imperfect clusters become problems.



III. Machine Learning
B. Classification Algorithms

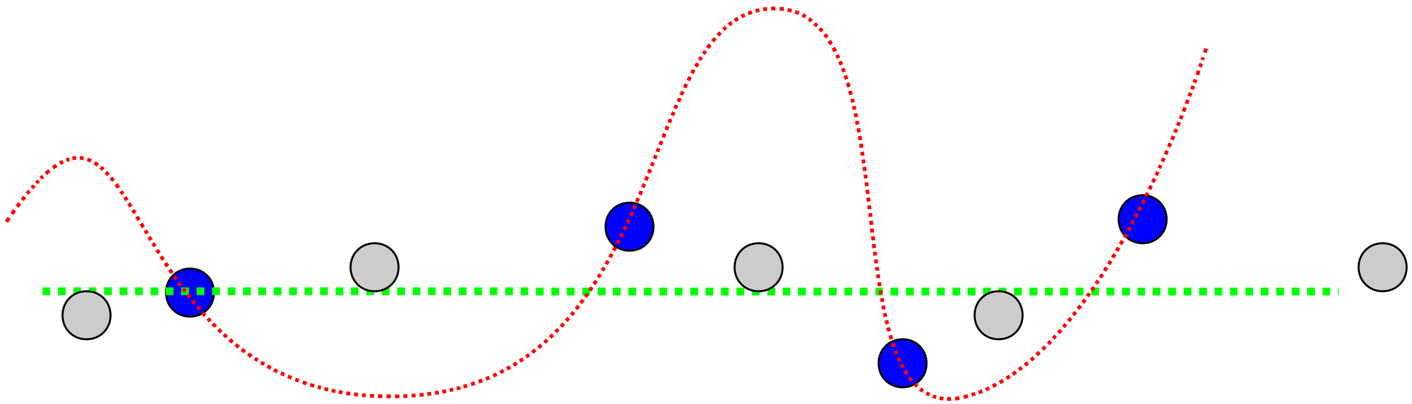
Transductive Clustering: Graph Cutter



III. B. Transductive Graph Cutter

Mean Accuracy: **97.8%**

But, possibly over-fitting



III. Machine Learning
B. Summary

Algorithm	Success
SMLR	**59%**
KNN	**75.7%**
Transductive Agglomerative	**12.99%**
Transductive Graph Cutting	**97.8%**

IV. Future Extensions

Machine Learning Approaches:

Additional Classification algorithms

- Bagging the good ones

- Encode the underlying assumption that each data entry of same ID should be classified the same.

Applications:

- In the way of a spell checker, an “attitude checker”

- Computational modeling of human cognition

Summary

I. Can computers learning social ques in text? **Yes**!

II. How do we obtain data? **WordSleuth**

a. Lots of data? **WordSleuth online**

b. Good data? **Taboo list**

III. How does a machine learn?

KNN, Transduction

IV. What's left to do

approaches and **applications**

References and Acknowledgments

Pearl, L. & Steyvers, M. (2010). *Identifying Emotions, Intentions, & Attitudes in Text Using a Game with a Purpose.* Proceedings of NAACL-HLT 2010 Workshop on Computational Approaches to Analysis and Generation of Emotion in Text. Los Angeles, CA: NAACL.

von Ahn, L. 2006. Games With A Purpose. IEEE Computer Magazine, June 2006: 96-98.

Waffles code repository: http://waffles.sourceforge.net

Questions?

Mutual Information

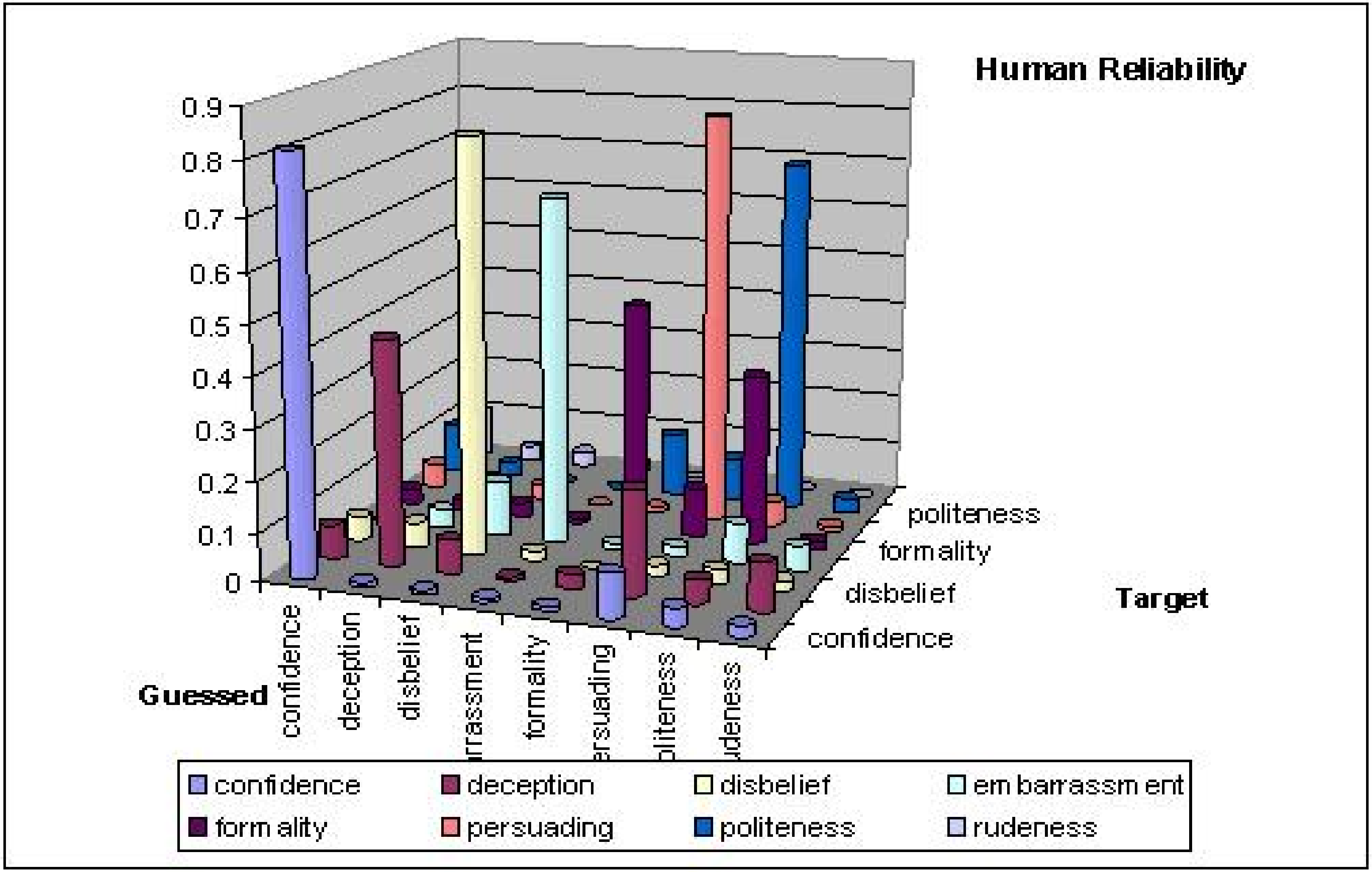
Mutual Information = log (p(x|y) / p(x))

For each word in the dataset

p(x) = the frequency of word **x** (in the data set)

p(y) = the frequency of social category **y** (in the dataset)

p(x|y) = the frequency of **x in y**



Human Reliability
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
politeness
formality
disbelief
confidence
Target
Guessed
confidence
deception
disbelief
rrassment
formality
ersuading
liteness
udeness
confidence
deception
disbelief
embarrassment
formality
persuading
politeness
rudeness