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# Extracting Diverse Sentiment Expressions With Target-dependent Polarity from Twitter

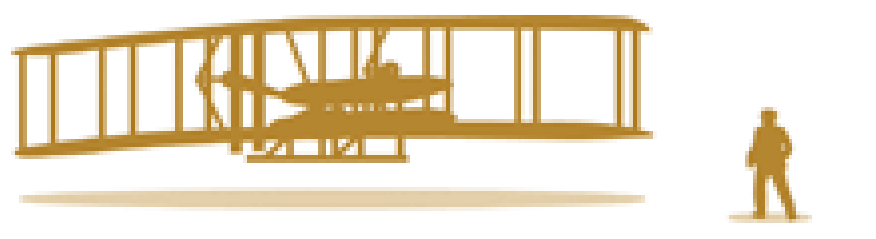
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## 1. Overview

This study focuses on **automatic extraction of sentiment expressions associated with given targets from Twitter**.

One of the key challenges: Wide **diversity** and **informal** nature of sentiment expressions that cannot be trivially enumerated or captured using predefined lexical patterns

Contributions:

- Extracting a **diverse** and **richer** set of sentiment-bearing expressions, including formal and slang words/phrases, not limited to pre-specified syntactic patterns
- Assessing the **target-dependent** polarity of each sentiment expression
- A novel formulation of assigning polarity to a sentiment expression as a **constrained optimization problem** over the tweet corpus

## 2. Extracting Candidate Expressions

**Root word:** a word that is considered sentiment-bearing in general sense.

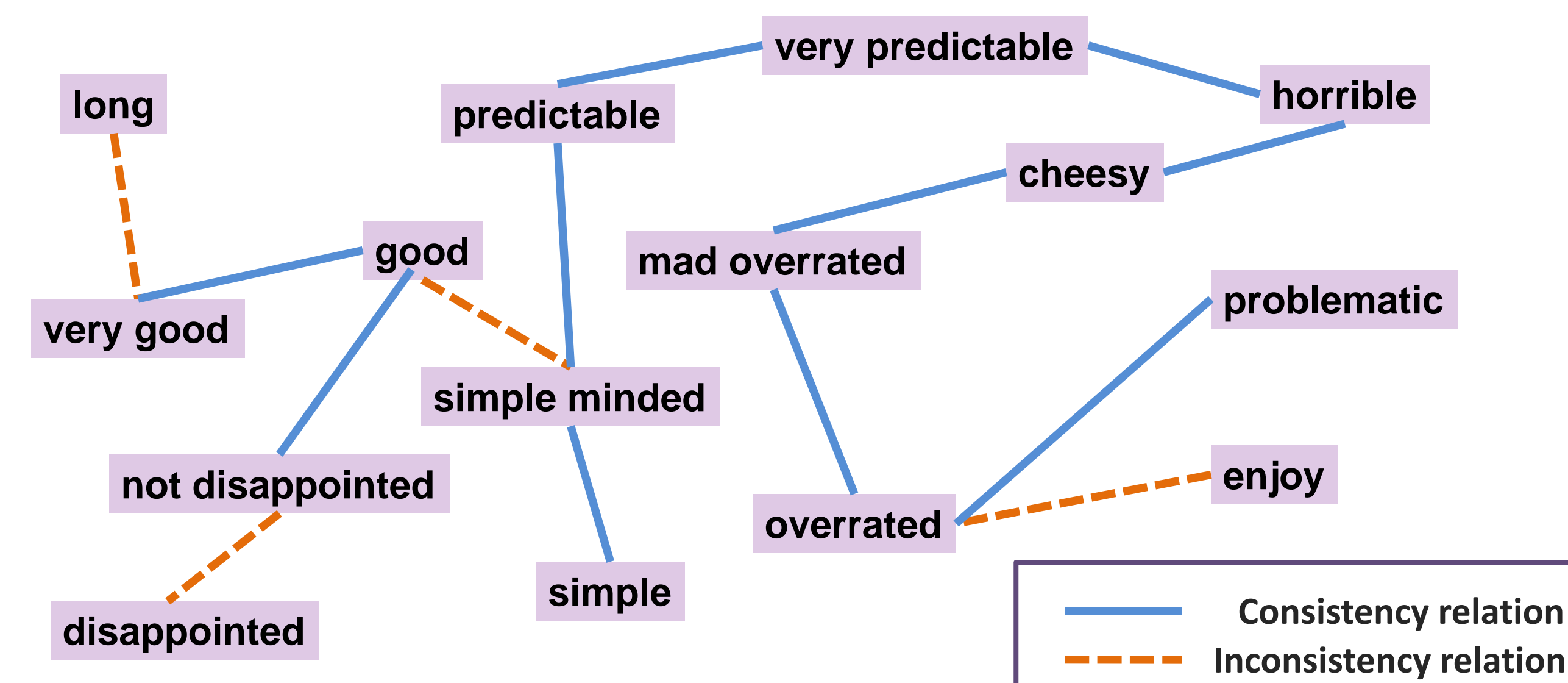
- Collecting root words from
  - MPQA, General Inquirer, and SentiWordNet (general-purpose sentiment lexicons)
  - Urban Dictionary (slang dictionary)
- For each tweet, selecting the **“on-target”** root words, and extracting all the n-grams that contain at least one selected root word as candidates

## 3. Identifying Inter-Expression Relations

Connecting the candidate expressions via two types of inter-expression relations – **consistency relation** and **inconsistency relation**

Example:

- I saw The Avengers yesterday evening. It was **long** **but** it was **very good**!
- I do **enjoy** The Avengers, **but** it's both **overrated** and **problematic**.
- Saw the avengers last night. **Mad overrated**. **Cheesy** lines and **horrible** writing. **Very predictable**.
- The avengers was **good** **but** the plot was just **simple minded** and **predictable**.
- The Avengers was **good**. I was **not disappointed**.



## 4. An Optimization Model

For each candidate expression  $C_i$ ,

- P-Probability**  $\Pr^P(C_i)$  – the probability that  $C_i$  indicates **positive** sentiment
- N-Probability**  $\Pr^N(C_i)$  – the probability that  $C_i$  indicates **negative** sentiment

$$\Pr^P(C_i) + \Pr^N(C_i) = 1$$

For each pair of candidate expressions  $C_i$  and  $C_j$ ,

- Consistency probability** – the probability that  $C_i$  and  $C_j$  have the same polarity:

$$\Pr^{cons}(C_i, C_j) = \Pr^P(C_i)\Pr^P(C_j) + \Pr^N(C_i)\Pr^N(C_j)$$

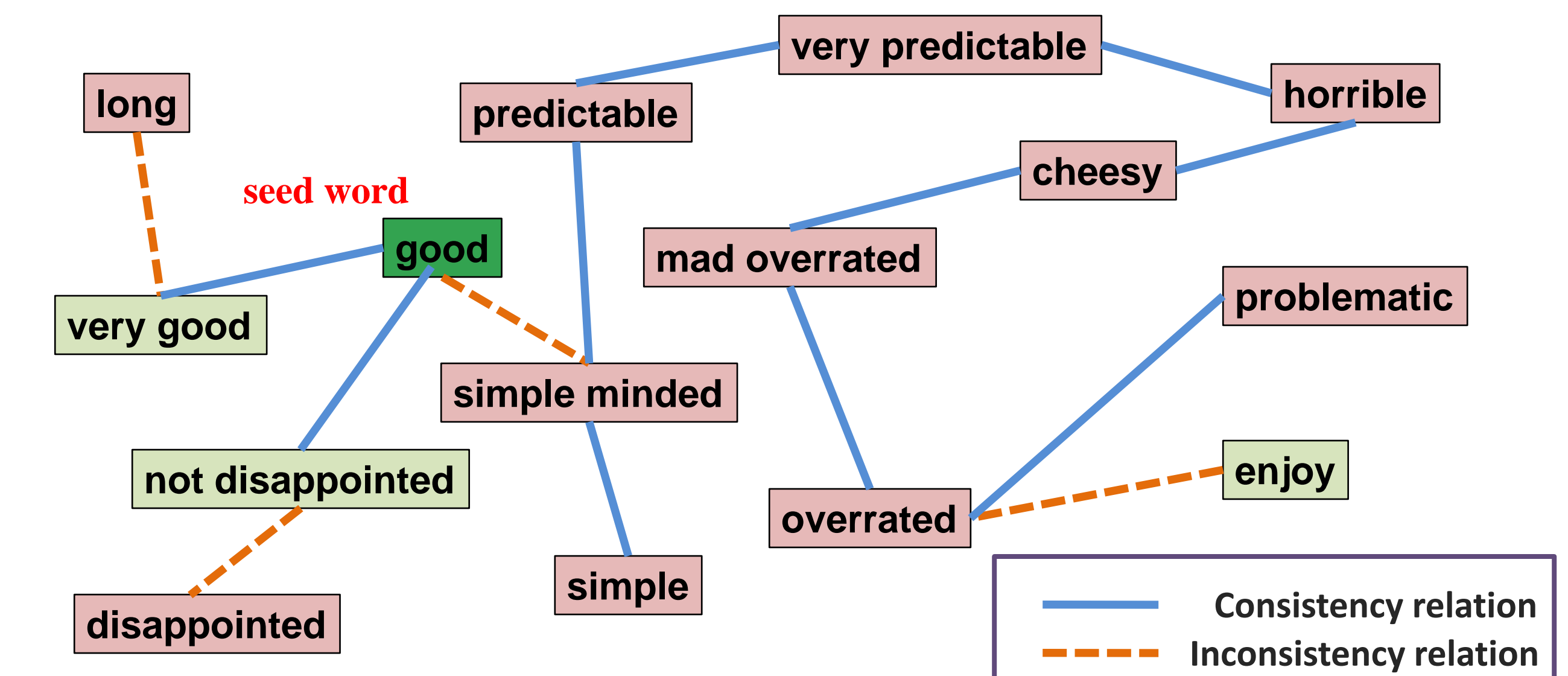
- Inconsistency probability** – the probability that  $C_i$  and  $C_j$  have different polarities:

$$\Pr^{incons}(C_i, C_j) = \Pr^P(C_i)\Pr^N(C_j) + \Pr^N(C_i)\Pr^P(C_j)$$

Objective Function:

$$\text{minimize} \left\{ \sum_{i=1}^{n-1} \sum_{j>i}^n \left( w_{ij}^{cons} (1 - \Pr^{cons}(C_i, C_j))^2 + w_{ij}^{incons} (1 - \Pr^{incons}(C_i, C_j))^2 \right) \right\}$$

where  $w_{ij}^{cons}$  and  $w_{ij}^{incons}$  are the weights of the edges (the frequency of the relations) between  $C_i$  and  $C_j$  in the **consistency** and **inconsistency** relation networks, and  $n$  is the total number of candidate expressions.



## Target-dependent Sentiment Expressions

Just saw **The Avengers**! It **lived up to the hype**. 😊 **positive expression**

Just got out of **the Avengers** movie. It was all storyboard, no story. 😞 **negative expression**

What a **clumsy, clunky mess**. Got kind of **bored** 90 min in. B- 😞

Went saw **The Avengers** tonight and man it was **epic**...a **definite must see!!!** 😊

President Obama watched **the Avengers**. 😊

**The Avengers** movie was **bloody amazing!** Mmm looking good Robert Downey Jr and Captain America ;) 😊

If I can be half as cool as Scarlett Johansson in **The Avengers** when I grow up, my life will be accomplished. 😊

Saw **the avengers** last night. **Mad overrated**. **Cheesy** lines and **horrible** writing. **Very predictable**. 😞

My best friend wants to see **The Avengers** today, so of course I'll go. Now to decide which Batman shirt to wear... 😊

Okay, **the Avengers** was **worth the hype**. **Best** superhero movie of all time. **Blown away**, here. 😊

## Distributions of N-grams and Part-of-speech of the Sentiment Expressions in the Gold Standard Data Set

N-gram	1	2	3	4	5	>5
Movie Domain	54.24%	21.02%	10.17%	6.44%	4.74%	3.39%
Person Domain	71.38%	17.75%	7.25%	1.81%	1.45%	0.36%

Part-of-speech	Adj.	Verb	Noun	Others
Movie Domain	57.63%	26.10%	13.22%	3.05%
Person Domain	45.29%	31.52%	21.02%	2.17%

## 5. Experimental Setup

Datasets:

- 168,005 tweets about **movies**
- 258,655 tweets about **persons**

Gold standard:

- 1,500 tweets labeled with sentiment expressions and overall polarities for the **movie** targets
- 1,500 tweets labeled with sentiment expressions and overall polarities for the **person** targets

Baseline methods:

- MPQA, GI, SWN:** For each extracted root word regarding the target, simply look up its polarity in MPQA, General Inquirer and SentiWordNet, respectively.
- PROP:** A propagation approach proposed by Qiu et al.
- COM-const:** Assign 0.5 to all the candidates as their initial P-Probabilities.
- COM-gelex:** Initialize the candidates' polarities according to the root word set.

Reference: Qiu, B., Liu, B., Bu, J., and Chen, C. 2009. Expanding domain sentiment lexicon through double propagation. In Proc. of IJCAI.

## Quality of the Extracted Sentiment Expressions

Method	Precision	Recall	F-measure
<b>Movie Domain</b>			
MPQA	0.3542	0.5136	0.4193
GI	0.3318	0.4320	0.3753
SWN	0.2876	0.4898	0.3624
PROP	0.4742	0.5034	0.4884
<b>COM-const</b>	<b>0.6433</b>	0.5170	<b>0.5733</b>
<b>COM-gelex</b>	0.5164	<b>0.5578</b>	0.5363
<b>Person Domain</b>			
MPQA	0.3523	0.4746	0.4045
GI	0.2949	0.4058	0.3416
SWN	0.2161	0.3659	0.2718
PROP	0.5352	0.3696	0.4372
<b>COM-const</b>	<b>0.5879</b>	0.4710	<b>0.5230</b>
<b>COM-gelex</b>	0.4599	<b>0.5507</b>	0.5012

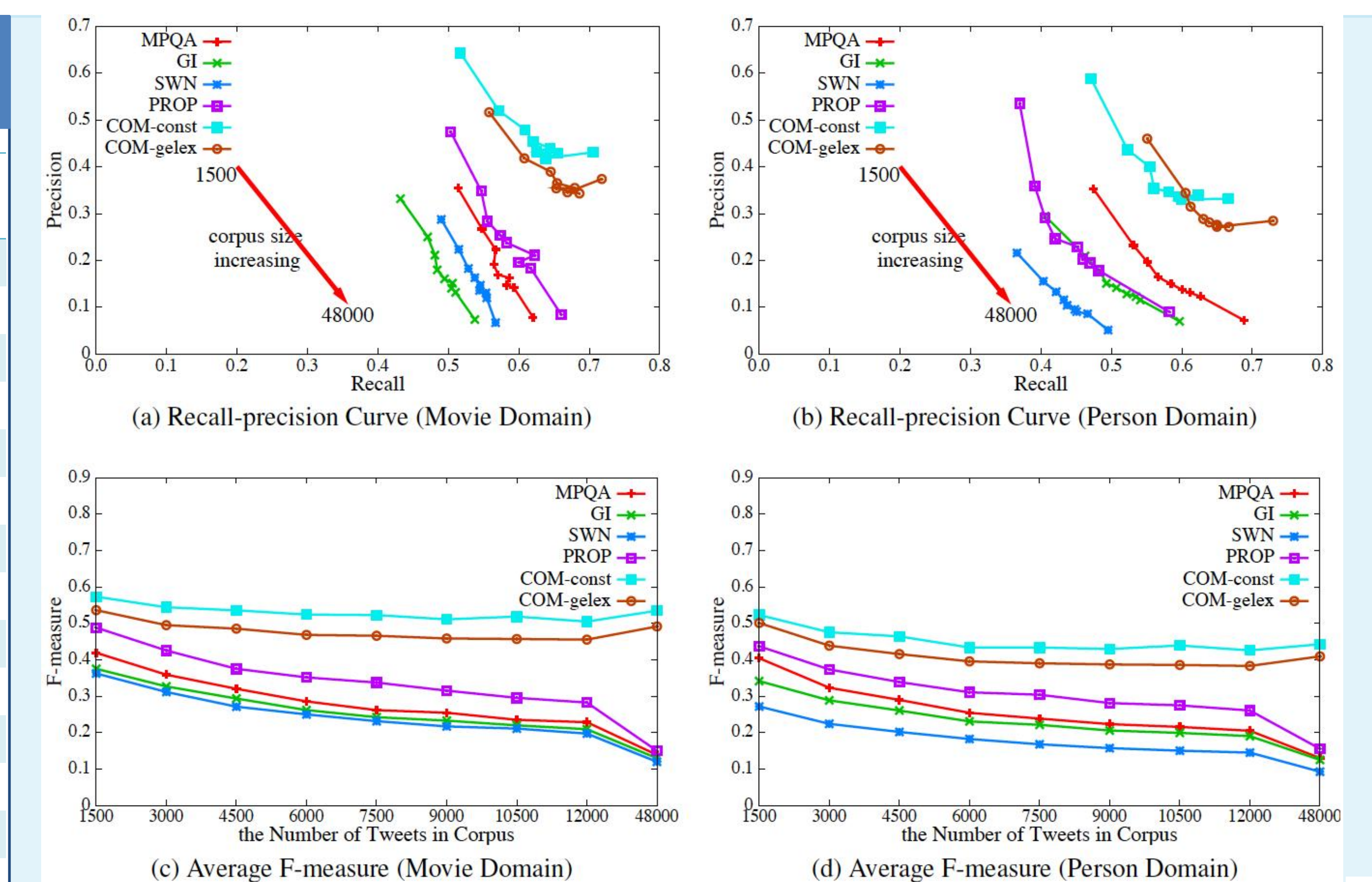


Figure 1: Results of Sentiment Expression Extraction with Various Corpora Sizes

