



# **Sentiment Analysis**

## **State of the Art in Research and Industry**

**Mark Cieliebak**

Zurich University of Applied Sciences

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# Mark Cieliebak

- + PhD in Theoretical Computer Science
- + IT Consultant in Major Swiss Bank
- + CIO at Netbreeze (bought by Microsoft)
- + >30 Publications

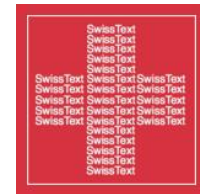


Lecturer



SPINNINGBYTES

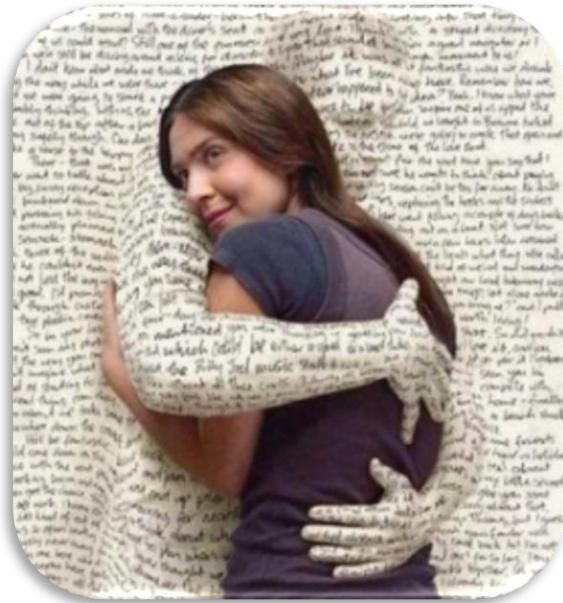
CEO



SwissText

Conference Chair

# Sentiment Analysis

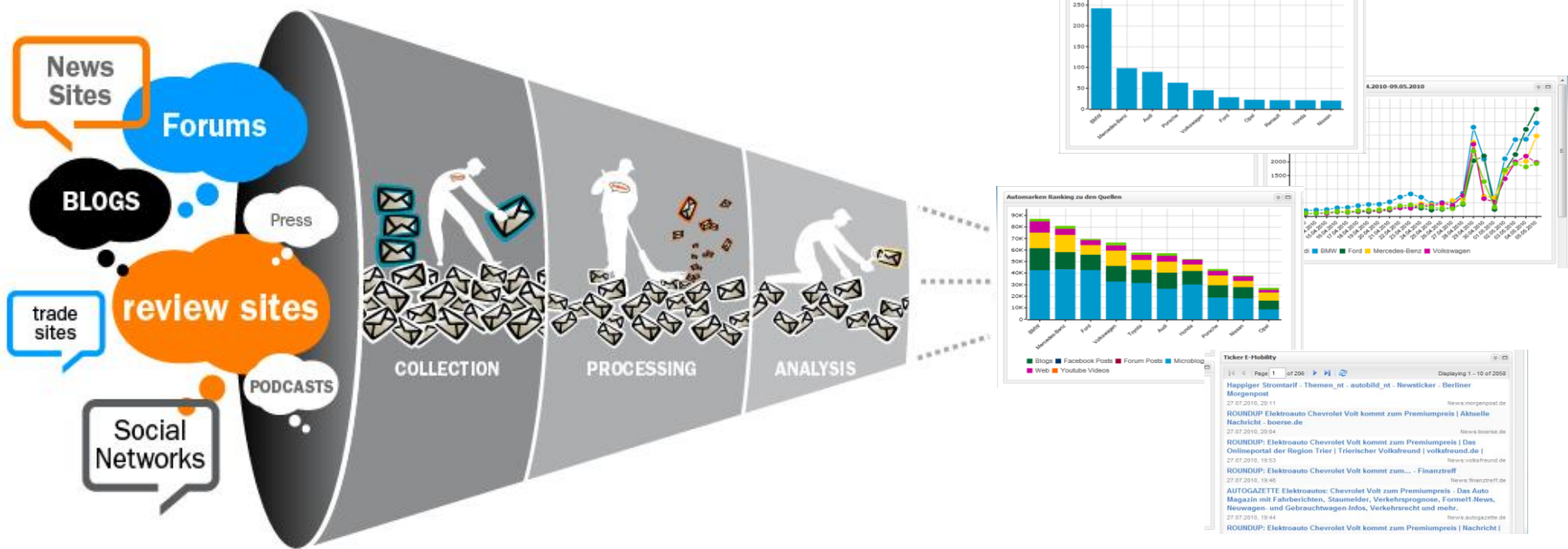


**Goal:** Decide whether a text expresses positive or negative emotion.

" This is a nice conference! "

# Insights for Marketing and Sales

Sentiment Analysis can identify trends in Social Media



# Characteristics of Sentiment Analysis

## Labels:

- Positive
- Negative
- Neutral
  
- Mixed
- (unknown)

## Tasks:

- Single sentence
- Complete document
  
- Specific aspect/target
  
- Quantification



# Sentiment-Analysis sounds easy

...but it isn't



@francesco\_con40 2nd worst QB. DEFINITELY Tony Romo. The man who likes to share the ball with everyone. Including the other team



@prodnose is this one of your little jokes like Elvis playing at the Marquee next Tuesday?



Tim Tebow may be available !  
Wow Jerry , what the heck you waiting for !  
<http://t.co/a7z9FBL4>



#YouCantDateMe if u still sag ur pants super hard...dat shit is played the fuck out!!!

# A Remark about Tool Quality

*"They all suck...and we suck, too."*

CEO of a sentiment analysis company (2013)

# Evaluation of Commercial Sentiment Analysis Tools in 2013

## 7 Text Corpora

- Single statements
- Various media types (tweet, news, reviews, speech transcripts etc.)
- Total: 28'653 texts

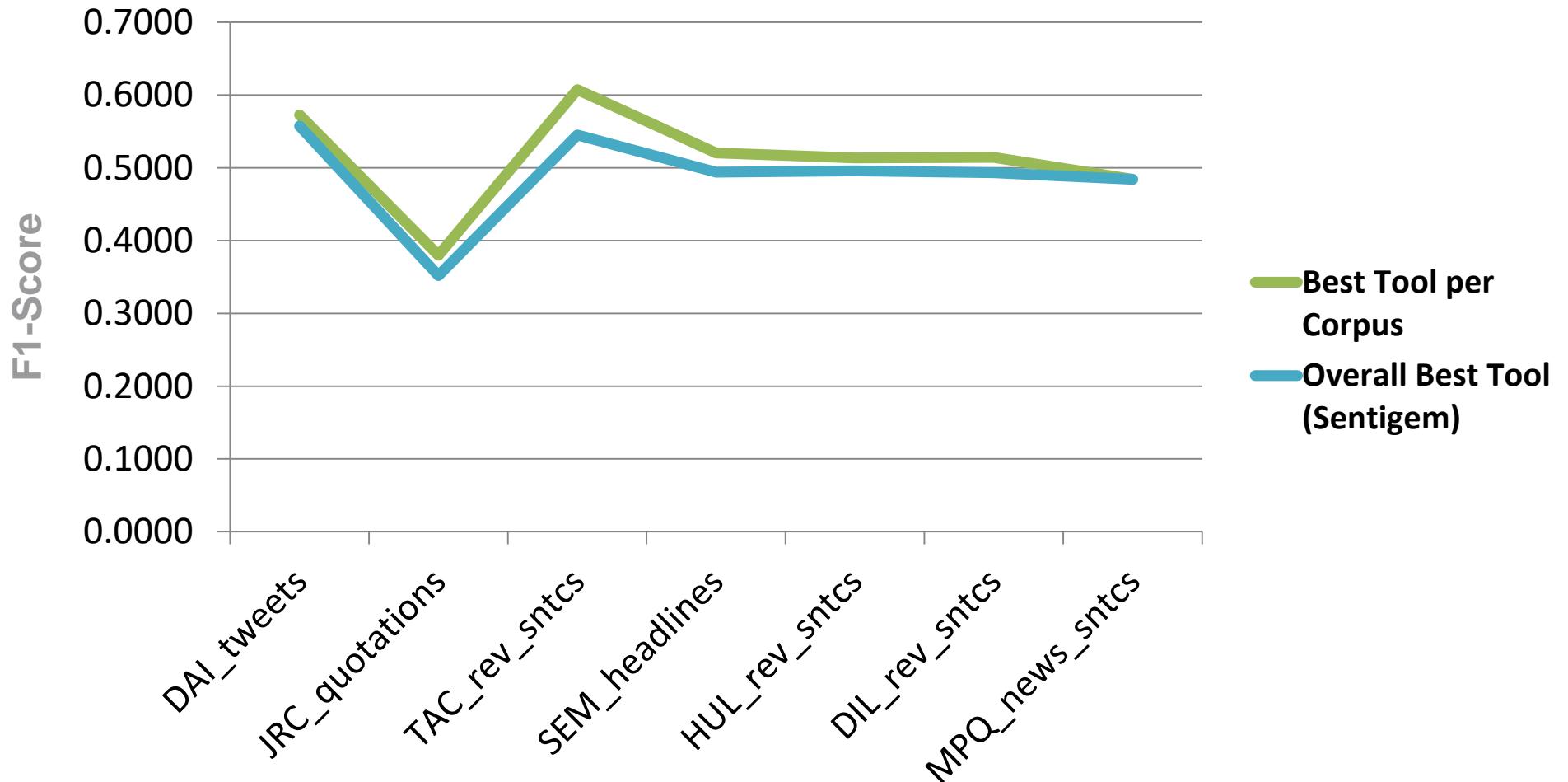
## 9 Commercial APIs

- Stand-alone
- Free for this evaluation
- English text



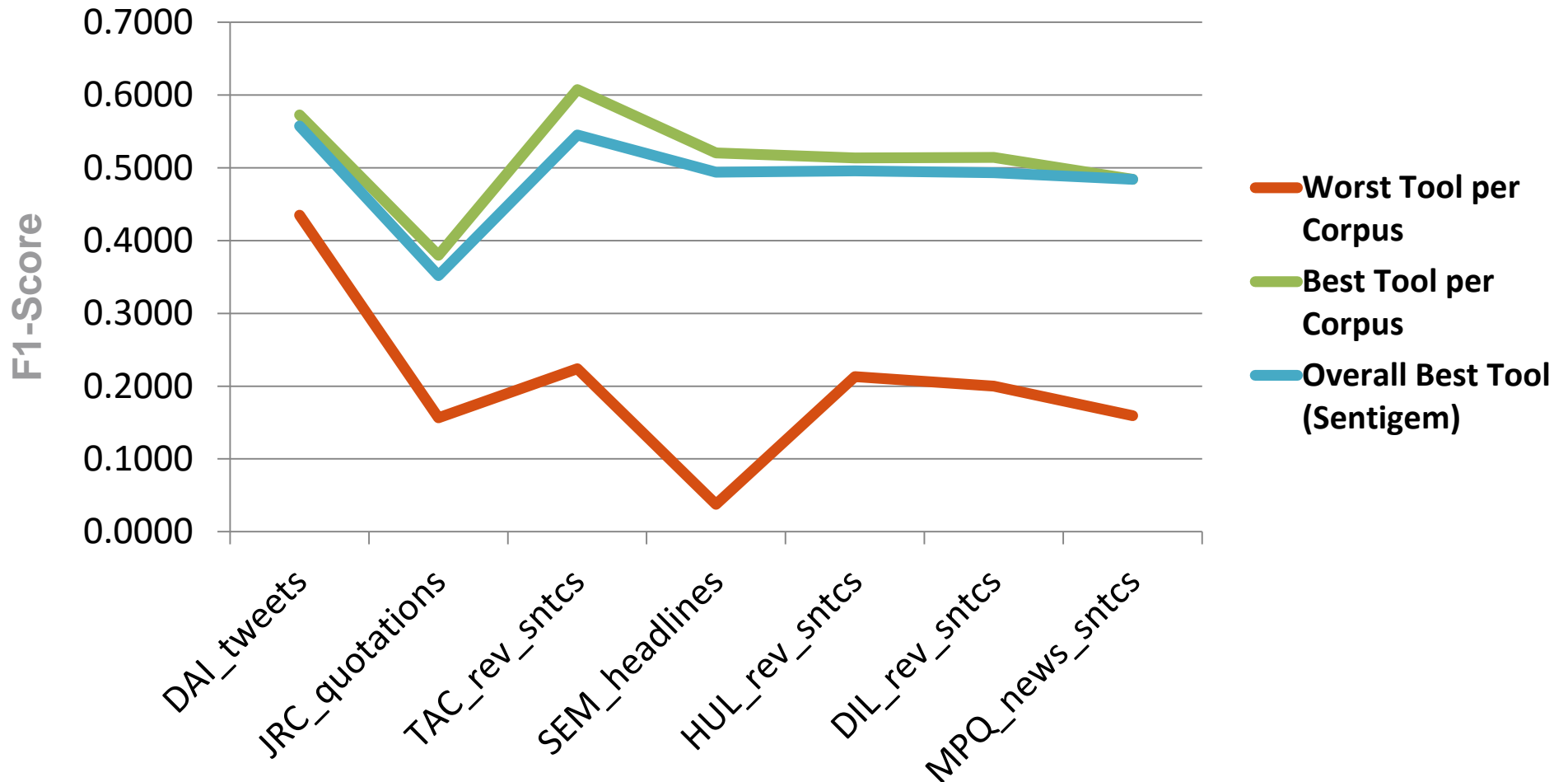


# Quality of Commercial Tools in 2013



Source: M. Cieliebak et al.: Potential and Limitations of Commercial Sentiment Detection Tools, ESSEM 2013.

# Quality of Commercial Tools in 2013



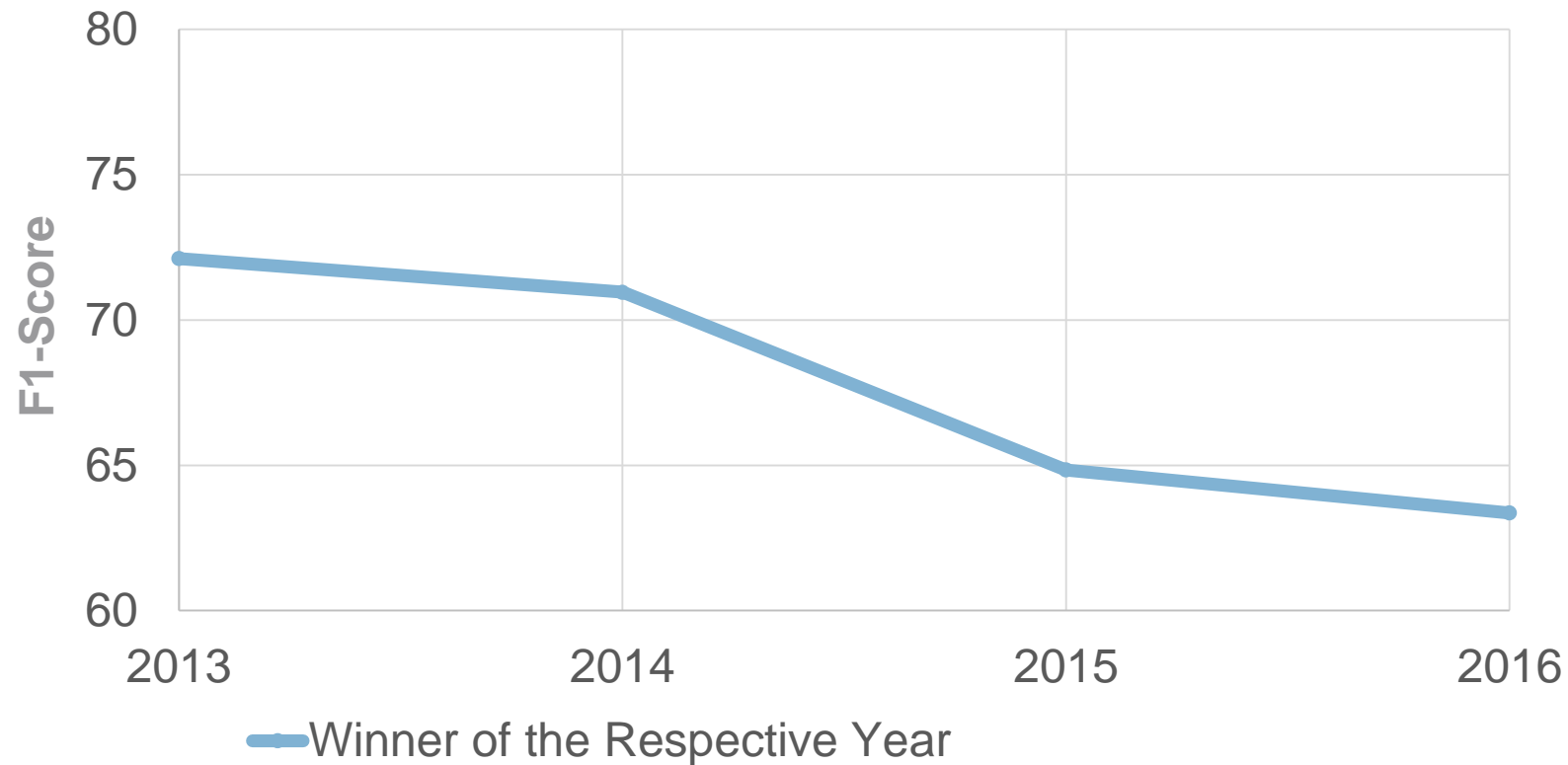
Source: M. Cieliebak et al.: Potential and Limitations of Commercial Sentiment Detection Tools, ESSEM 2013.

# SemEval: International Competition for Sentiment Analysis

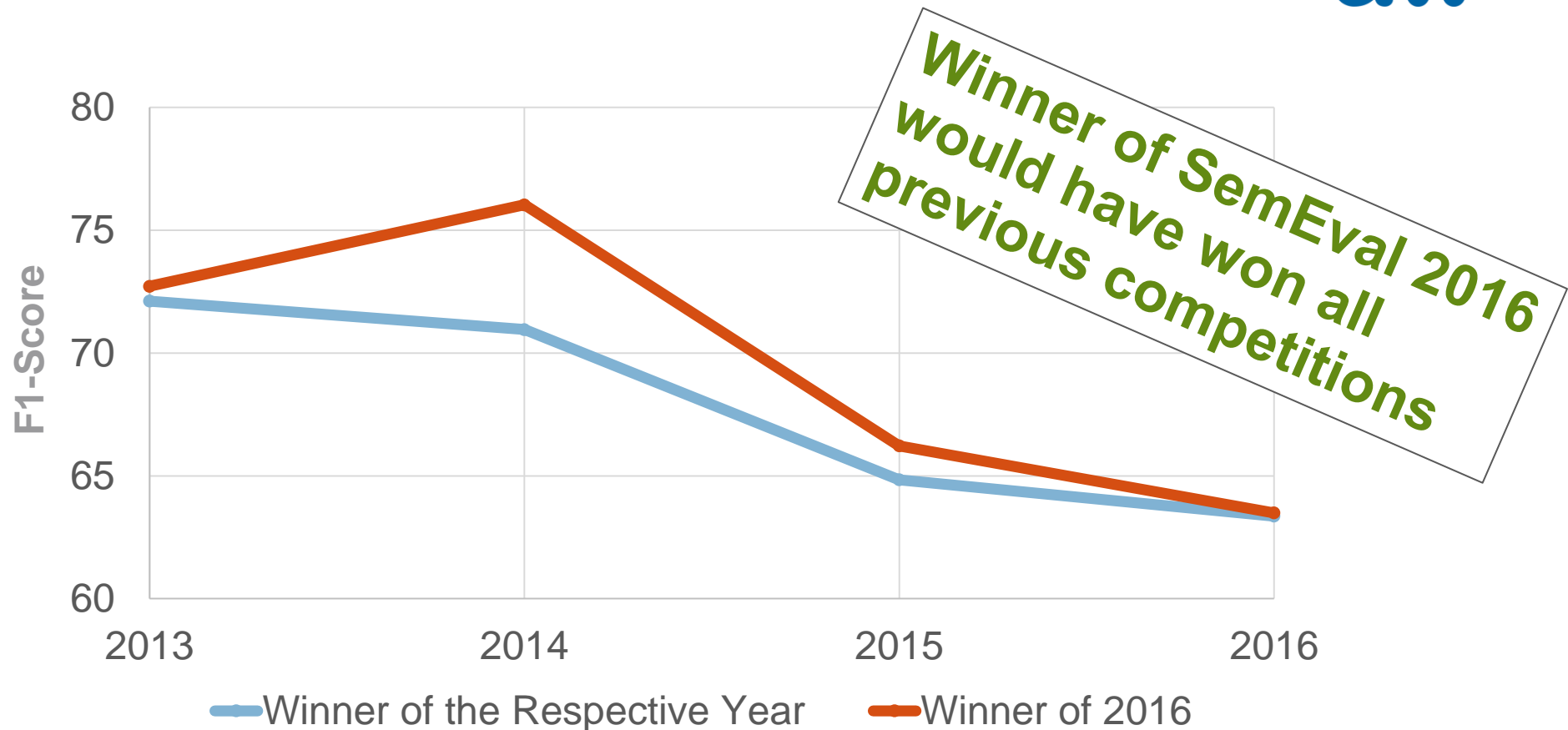
**Task:** Build a system for sentiment analysis (pos, neg, neutral) on tweets in English

Year	Winning Team	F1-Score	Winning Technology	Remarks
2013	NRC Canada	<b>69.02</b>	Features + large dictionaries	First run of the competition
2014	TeamX	<b>72.12</b>	Similar approach as in 2013	First two participants using deep learning
2015	Webis	<b>64.84</b>	Ensemble of 4 approaches from previous years	
2016	SwissCheese	<b>63.30</b>	CNN+Distant Supervision	30'000 new tweets Dominance of deep learning among submissions

# Did Sentiment Technology Improve?



# Did Sentiment Technology Improve?

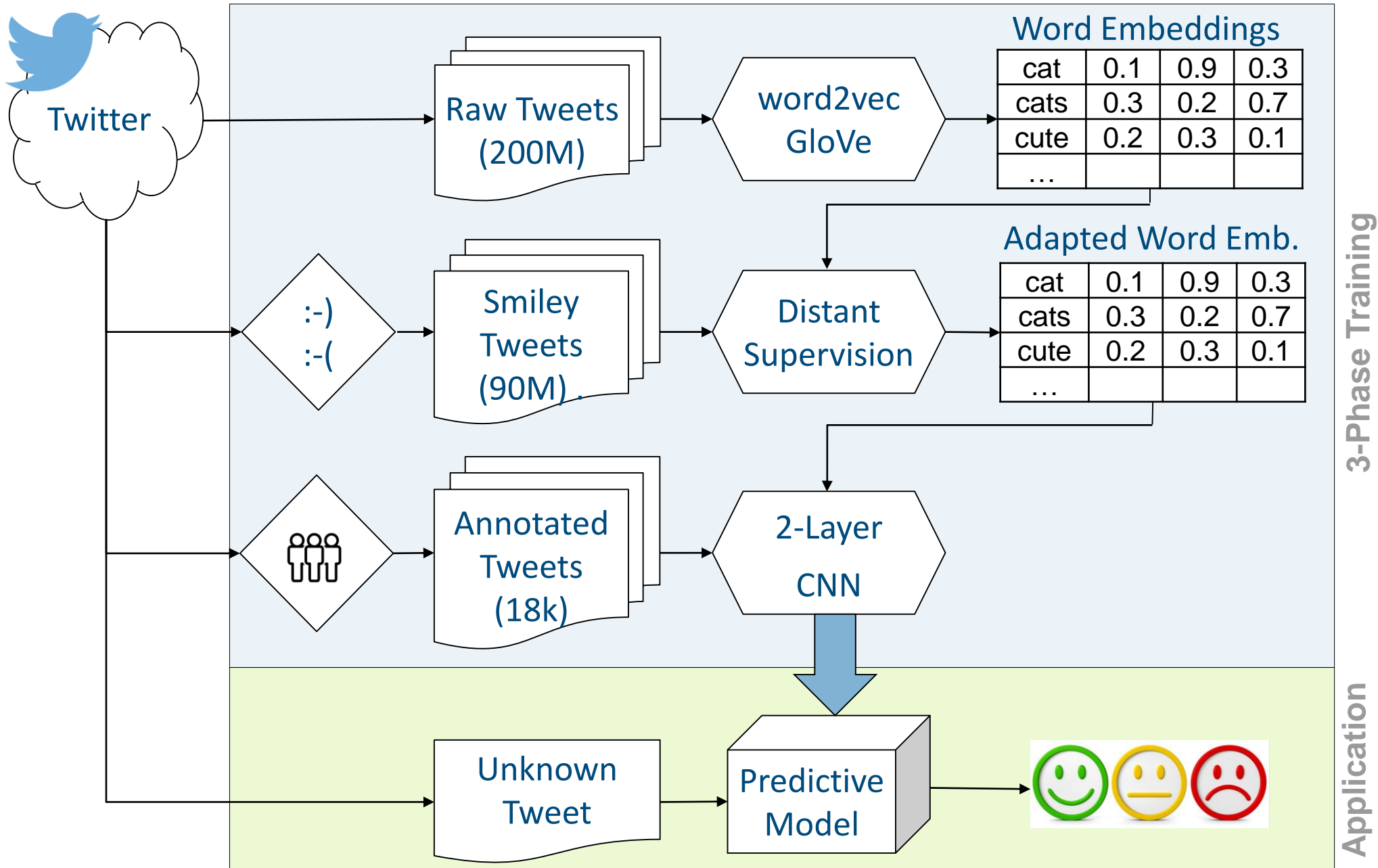


Red line: performance of SemEval winner from 2016 (SwissCheese)  
if only trained on training data for each year

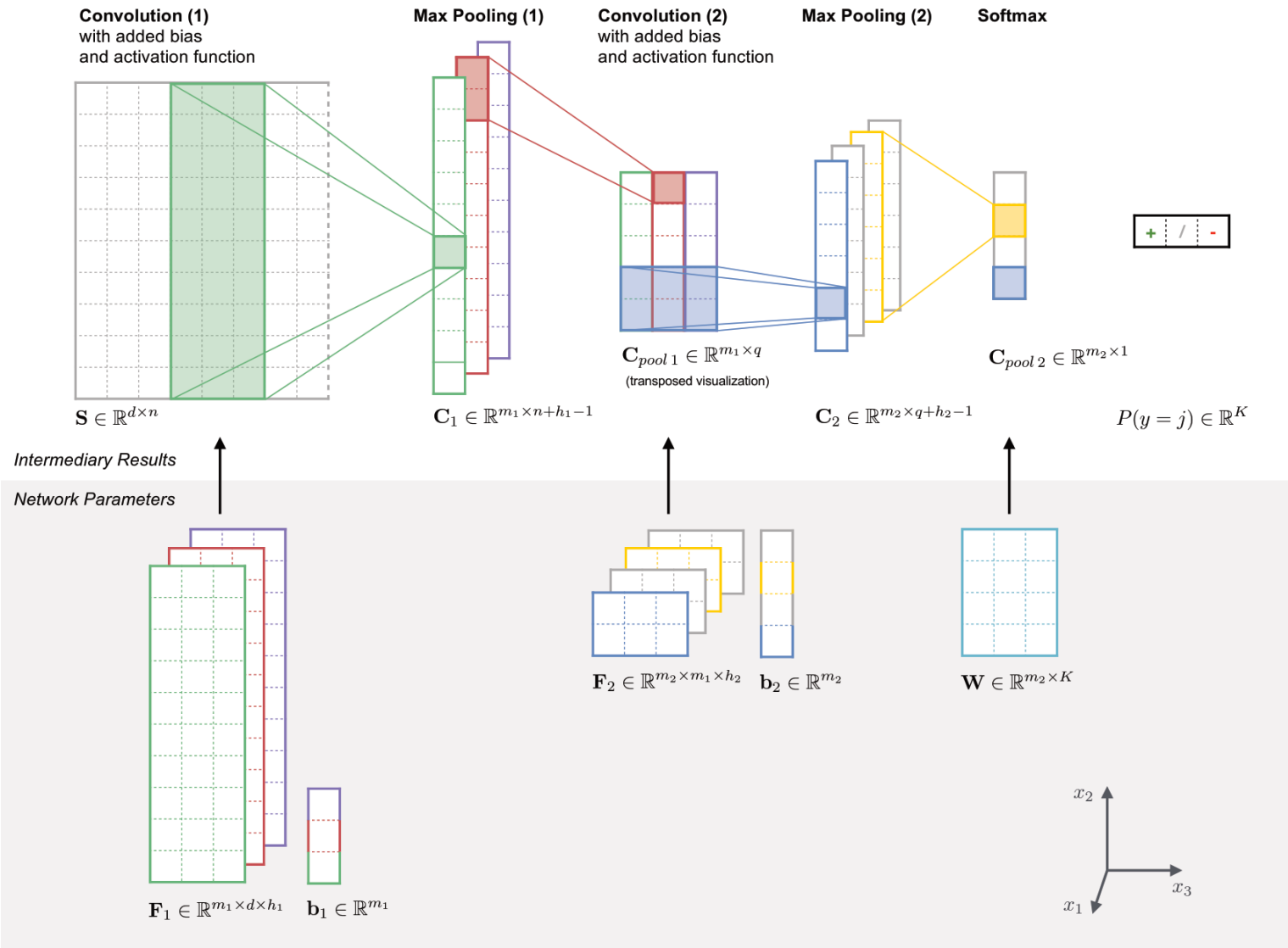
# A Shallow Dive into Technology



# SwissCheese: 3-Phase Training with Distant Supervision

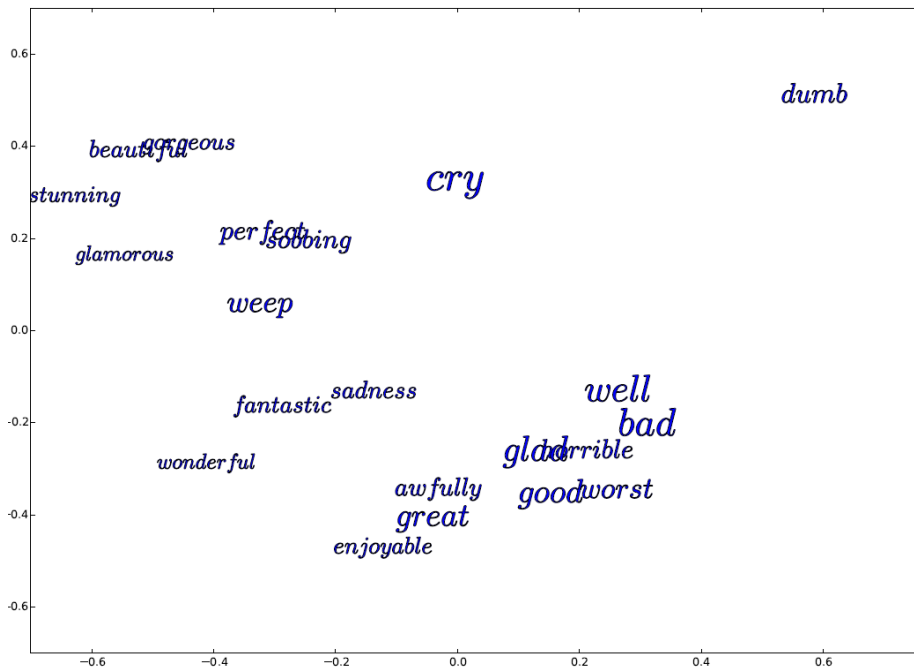


# 2-Layer Convolutional Neural Network for Sentiment Analysis

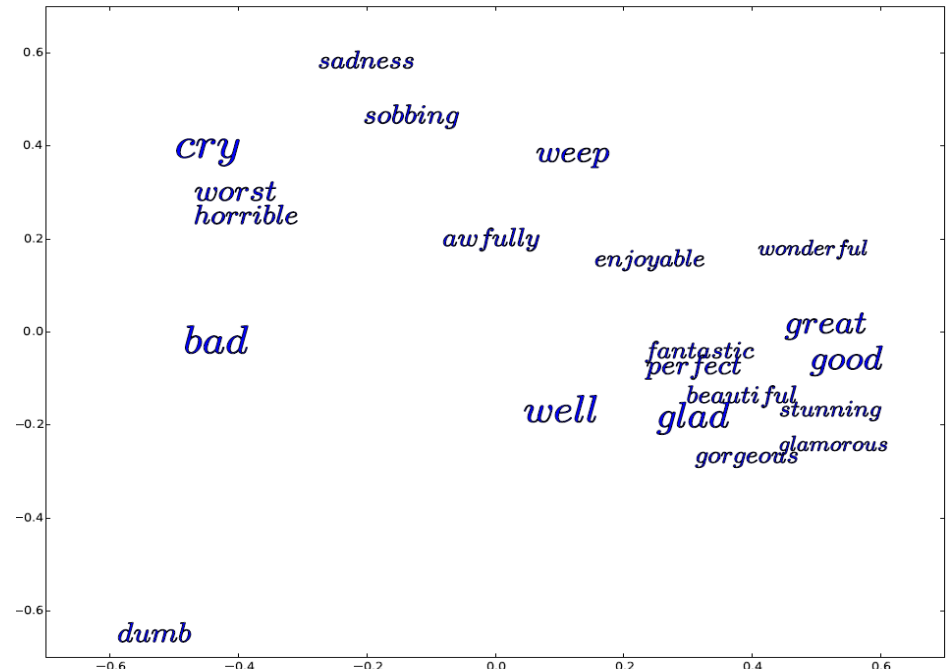




# Distant Phase rearranges Word Embeddings

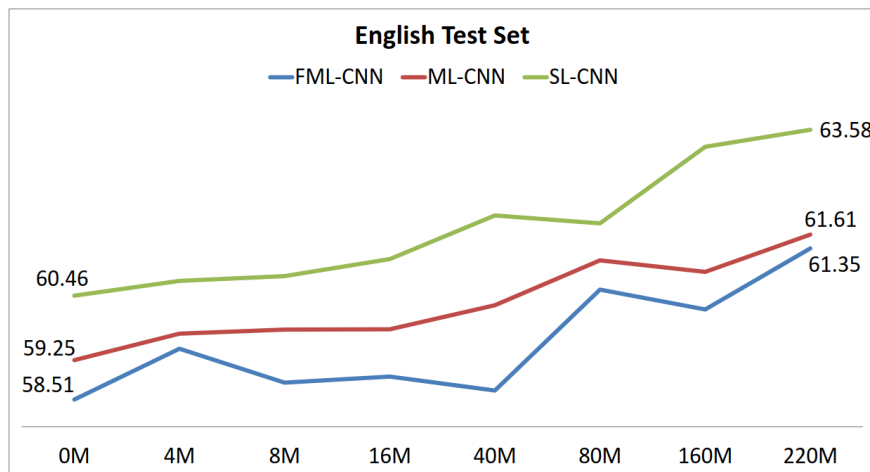


Before the Distant Phase

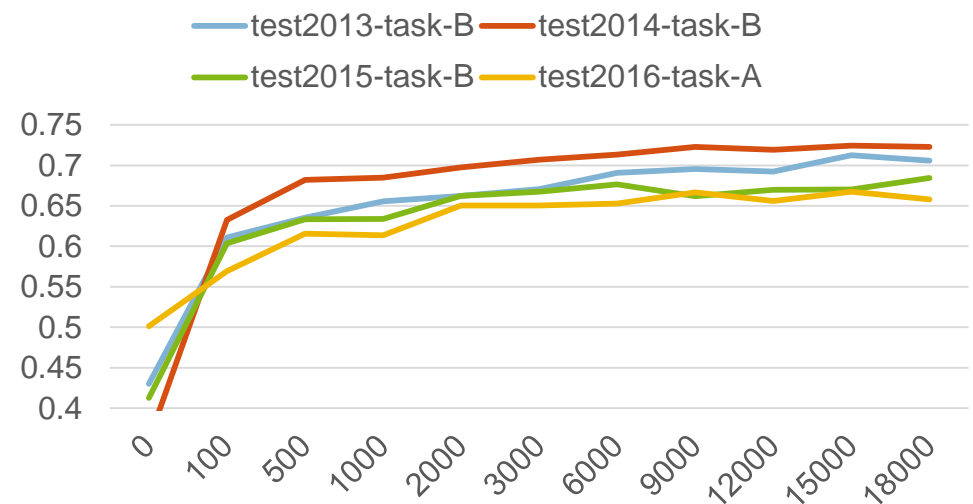


After the Distant Phase

# The More Data, The Better!



Number of tweets in distant phase



Number of annotated tweets

# Learn on Tweets, Classify News?

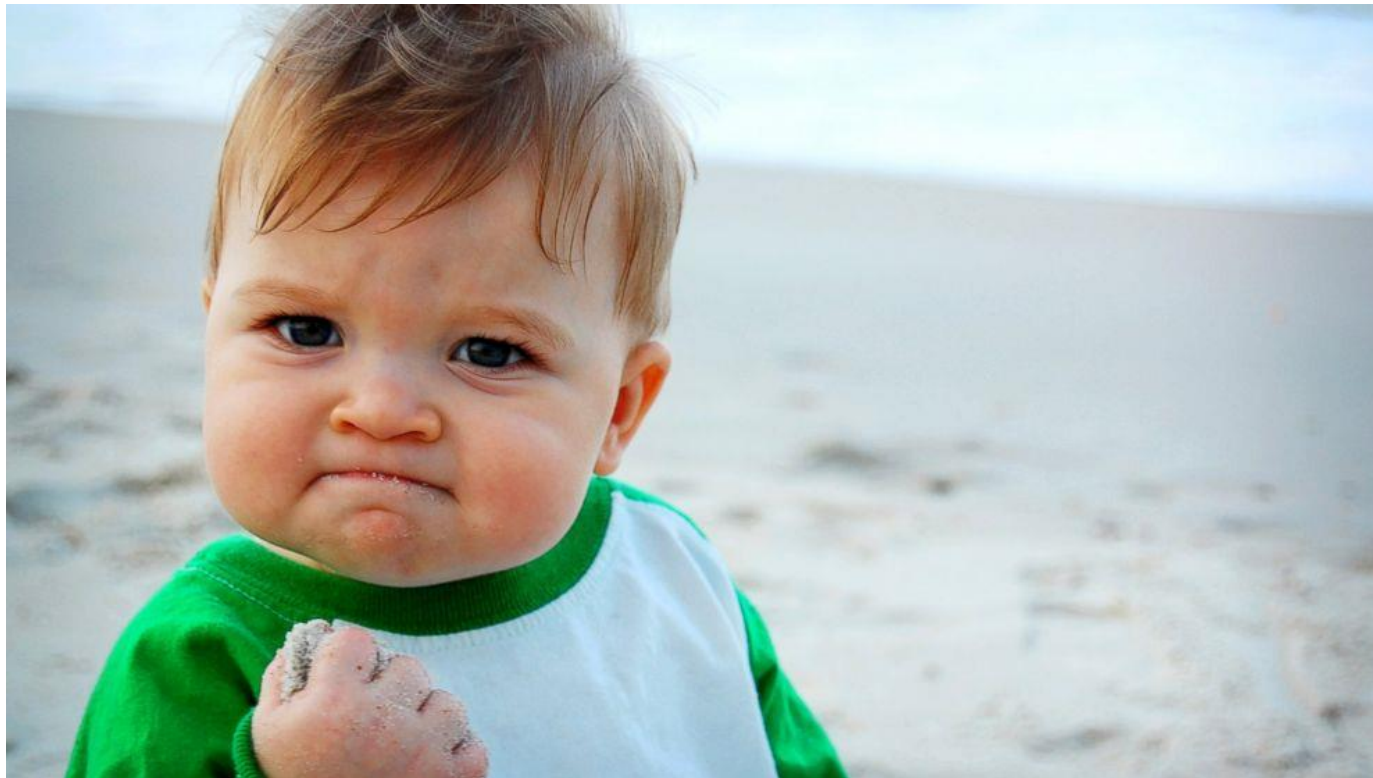
test train	SemEval'13_tweets	MPQ_reviews	DIL_reviews	DAI_tweets	Union of All Test Data
SemEval'13_tweets	72.4	45.8	53.1	62.2	63.9
MPQ_reviews	62.2	<b>54.1</b>	40.9	57.8	58.7
DIL_reviews	57.3	36.8	<b>55.1</b>	48.5	52.9
DAI_tweets	67.9	37.7	50.4	70.8	60.4
Union of All Training Data	<b>73.0</b>	50.8	49.9	<b>76.6</b>	<b>66.6</b>

Measured in F1 score

## Cross-Domain Performance of SemEval Winner 2016

# Sentiment for other Languages

Language	Available Data	Best Know Result (F1 Score)	Reference
German	10'000 Tweets	64.19	Deriu et al., 2016, WSDM (submitted)
Spanish	68'000 Tweets	71.1 (precision)	Villena-Roman et al., 2013, Procesamiento del Lenguaje Natural
Italian	7'000 Tweets	65.87	Deriu et al., 2016, WSDM (submitted)
Dutch	1'100 Tweets (labeled pos/neg)	88.33	Deriu et al., 2016, WSDM (submitted)
Arabic	1'100 Tweets	73.5	Salab et al., 2015, ANLP



**We did it: Theory is over!**

# Do It Yourself: Sentiment Analysis Tools and APIs

## Big Players

- Google Prediction API
- IBM AlchemyAPI
- Microsoft Azure Text Analytics API

## NLP Specialists

- RapidMiner
- Repustate
- Semantria
- SentiStrength
- SpinningBytes

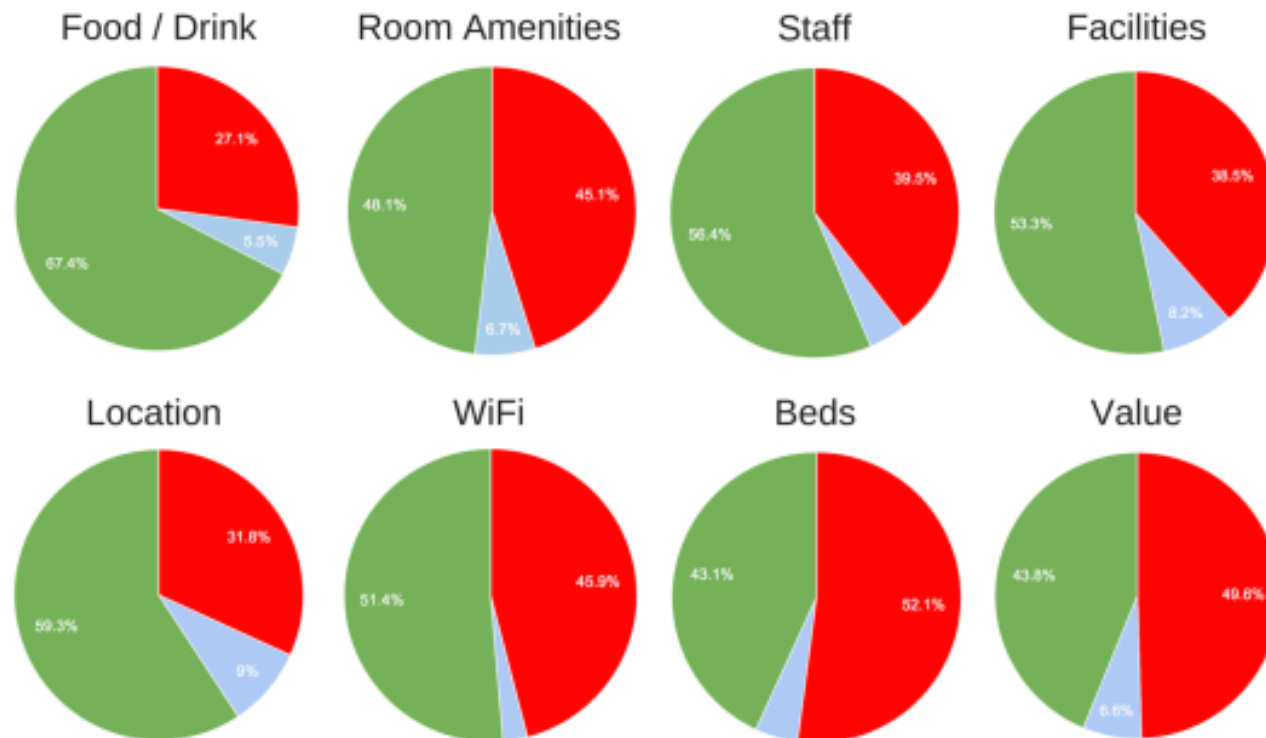
## Development Toolkits

- Natural Language ToolKit NLTK (Python)
- StanfordNLP (Java)



# Understand Customer Reviews

Example: Aspect-based Sentiment Analysis for Hotel Reviews

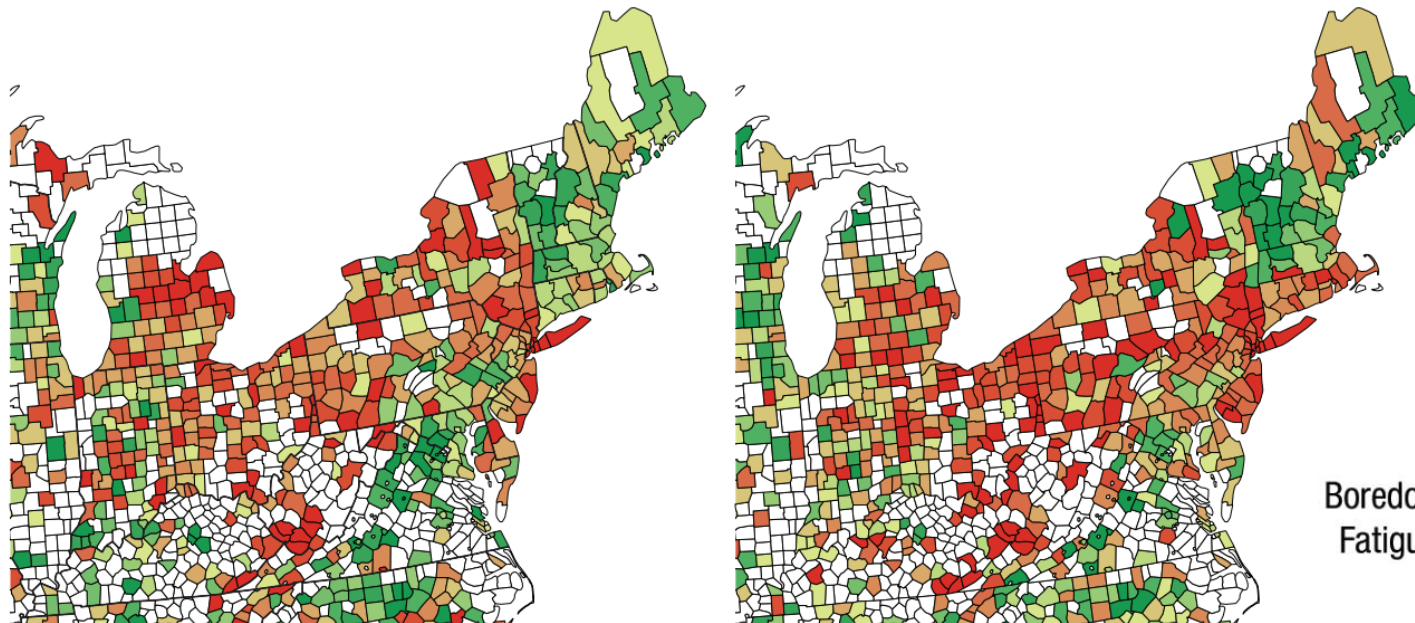


Source: <http://blog.aylien.com/aspect-based-sentiment-analysis-now-available-in/>

# Use Twitter to predict Heart Disease Mortality

CDC-Reported AHD Mortality

Twitter-Predicted AHD Mortality



10 20 30 40 50 60 70 80 90

AHD Mortality (Percentile)

Boredom,  
Fatigue



Optimism



Source: Eichstaedt et al., 2015: Psychological Language on Twitter Predicts County-Level Heart Disease Mortality



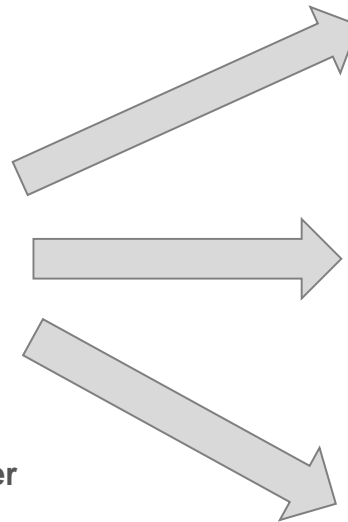
# "Cleantechness" of Company Products



Company Website



Automatic Classifier



## Cleantech Topics



Disaster Prevention



Energy Transportation



Energy Production



Energy Efficiency



Mobility



Air and Environment

# Age and Gender of "Anonymous" Users

**Goal:** Predict age (18-24, 25-34, 35-49, 50+) and gender (male/female) of Twitter users

**Results PAN 2015:**

Age: 86%

Gender: 84%



# Talk in Short!

## Sentiment Analysis

- **approx. 70% F1-score**
- **the more data – the better**
- **has important application**



# Thanks!!



**Mark Cieliebak**

**Zurich University of Applied Sciences (ZHAW)**

Email: [ciel@zhaw.ch](mailto:ciel@zhaw.ch), Website: [www.zhaw.ch/~ciel](http://www.zhaw.ch/~ciel)

This presentation is based on joint work with:

- Aurelien Lucchi, ETH
- Dominic Egger, ZHAW
- Fatih Uzdilli, ZHAW
- Jan Deriu, ZHAW
- Leon Derczynski, Univ. of Sheffield
- Martin Jaggi, EPFL
- Maurice Gonzenbach, ZHAW
- Valeria de Luca, ETH