# Text Classification in the Wild

CS 490A, Fall 2021

Applications of Natural Language Processing

https://people.cs.umass.edu/~brenocon/cs490a_f21

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# Administrivia

- HW1 grades have been released
- HW2 Annotated dataset due tonight!
- Final submission due Friday

# Text Classification

Input: some text ***x*** (e.g. sentence, document)

Output: a label ***y*** (from some finite label set)

Goal: learn a mapping function ***f*** from ***x*** to ***y***

# Thumbs up?
## Sentiment Classification using Machine Learning Techniques

Core Question:

Can machine learning techniques be used to classify documents by overall sentiment?

Pang et al. 2002

# Why might this be a hard task?

Pang et al. 2002

# Why might this be a hard task?

"How could anyone sit through this movie?"

Pang et al. 2002

# Why might this be a hard task?

"This film *should* be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is *attempting* to deliver a good performance. However, it *can't* hold up."

"I *hate* the Spice Girls. ...[3 things the author hates about them]... Why I saw this movie is a really, really, really long story, but I did, and one would think I'd *despise* every minute of it. But... Okay, I'm really *ashamed* of it, but I enjoyed it. I mean, I admit it's a *really awful* movie ...the ninth floor of *hell*...The plot is such a *mess* that it's *terrible*. But I loved it."

Pang et al. 2002

# Dataset

IMDB reviews: 700 positive (+), 700 negative (−)

Available at: cs.cornell.edu/people/pabo/movie-review-data/

Labels:

- Extracted from review text
- Label strongly positive reviews as +
- Label strongly negative reviews as −
- Others considered neutral and discarded

Pang et al. 2002

# Dataset

Data Curation:

- For each author, only include at most 20 + and 20 – reviews
- Extract text from html
- Remove explicit ratings ("*** out of *****") & boilerplate text
- Treat punctuation as individual tokens
- Lowercase text

```
these are words that could be used to describe the
emotions of john sayles' characters in his latest
, limbo . but no , i use them to describe myself
after sitting through his latest little exercise
in indie egomania . i can forgive many things .
but using some hackneyed , whacked-out , screwed-
up * non * -ending on a movie is unforgivable . i
walked a half-mile in the rain and sat through two
hours of typical , plodding sayles melodrama to
get cheated by a complete and total copout finale
. does sayles think he's roger corman ?
```

Pang et al. 2002

# Even preexisting datasets can be messy

```
filmcritic . com presents a review from staff member james brundage . you can find the
review with full credits at http : //filmcritic . com/misc/emporium .
nsf/2a460f93626cd4678625624c007f2b46/c97ebb11df0b98398825694f005571d7 ? opendocument he
is duncan macleod of the clan macleod . he's been pimpin' it since he was born in the
village of glennfillan in 15somethingsomething , and he continues to pimp it in modern
day . he is immortal and he cannot die .
```

```
all of my film reviews are archived at http : //us . imdb . com/m/reviews_by ? justin + felix
this review has been submitted to the shrubbery http : //www . theshrubbery . com any comments
about this review ? e-mail me at justinfelix@yahoo . comscreen story by kevin yagher and andrew
kevin walker . inspired by the short story the legend of sleepy hollow by washington irving .
```

```
1939 , g , 222 minutes [3 hours , 42 minutes] starring : viven leigh ( katherine scarlett o'hara-
hamilton-kennedy-butler ) , clark gable ( captain rhett butler ) , olivia de havilland ( melanie
wilkes ) , leslie howard ( ashley wilkes ) ; written by sidney howard ; produced by david o .
selznik ; directed by victor fleming ; based on the novel by margaret mitchell . seen july 8 ,
1998 at the crossgates cinema 18 , ( albany , ny ) , theater #7 , at 8 : 15 p . m . with my mom
using hoyts cinema cash . [theater rating : * * * 1/2 : very good sound , picture , and seats]
```

Pang et al. 2002

# Even preexisting datasets can be messy

−

filmcritic . com presents a review from staff member james brundage . you can find the review with full credits at http : //filmcritic . com/misc/emporium . nsf/2a460f93626cd4678625624c007f2b46/c97ebb11df0b98398825694f005571d7 ? opendocument he is duncan macleod of the clan macleod . he's been pimpin' it since he was born in the village of glennfillan in 15somethingsomething , and he continues to pimp it in modern day . he is immortal and he cannot die .

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Pang et al. 2002

# Word List Baselines

| Baseline | Proposed word lists | Accuracy | Ties |
|---|---|---|---|
| Human 1 | +: dazzling, brilliant, phenomenal, excellent, fantastic<br>−: suck, terrible, awful, unwatchable, hideous | 58% | 75% |
| Human 2 | +: gripping, mesmerizing, riveting, spectacular, cool, awesome, thrilling, badass, excellent, moving, exciting<br>−: bad, cliched, sucks, boring, stupid, slow | 64% | 39% |

Pang et al. 2002

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| Human 3 + stats | +: love, wonderful, best, great, superb, still, beautiful<br>−: bad, worst, stupid, waste, boring, ?, ! | **69%** | 16% |

Pang et al. 2002

# Results

| | Features | # of features | frequency or presence? | NB | ME | SVM |
|---|---|---|---|---|---|---|
| (1) | unigrams | 16165 | freq. | **78.7** | N/A | 72.8 |
| (2) | unigrams | " | pres. | 81.0 | 80.4 | **82.9** |
| (3) | unigrams+bigrams | 32330 | pres. | 80.6 | 80.8 | **82.7** |
| (4) | bigrams | 16165 | pres. | 77.3 | **77.4** | 77.1 |
| (5) | unigrams+POS | 16695 | pres. | 81.5 | 80.4 | **81.9** |
| (6) | adjectives | 2633 | pres. | 77.0 | **77.7** | 75.1 |
| (7) | top 2633 unigrams | 2633 | pres. | 80.3 | 81.0 | **81.4** |
| (8) | unigrams+position | 22430 | pres. | 81.0 | 80.1 | **81.6** |

Figure 3: Average three-fold cross-validation accuracies, in percent. Boldface: best performance for a given setting (row). Recall that our baseline results ranged from 50% to 69%.

Pang et al. 2002

# Sentiment expression varies across domains

| domain\polarity | negative | positive |
|---|---|---|
| books | plot <num>_pages predictable<br>reading_this page_<num> | reader grisham engaging<br>must_read fascinating |
| kitchen | the_plastic poorly_designed<br>leaking awkward_to defective | excellent_product espresso<br>are_perfect years_now a_breeze |

Table 2: Correspondences discovered by SCL for books and kitchen appliances. The top row shows features that only appear in books and the bottom features that only appear in kitchen appliances. The left and right columns show negative and positive features in correspondence, respectively.

Blitzer et al. 2007

# Sentiment expression varies across domains

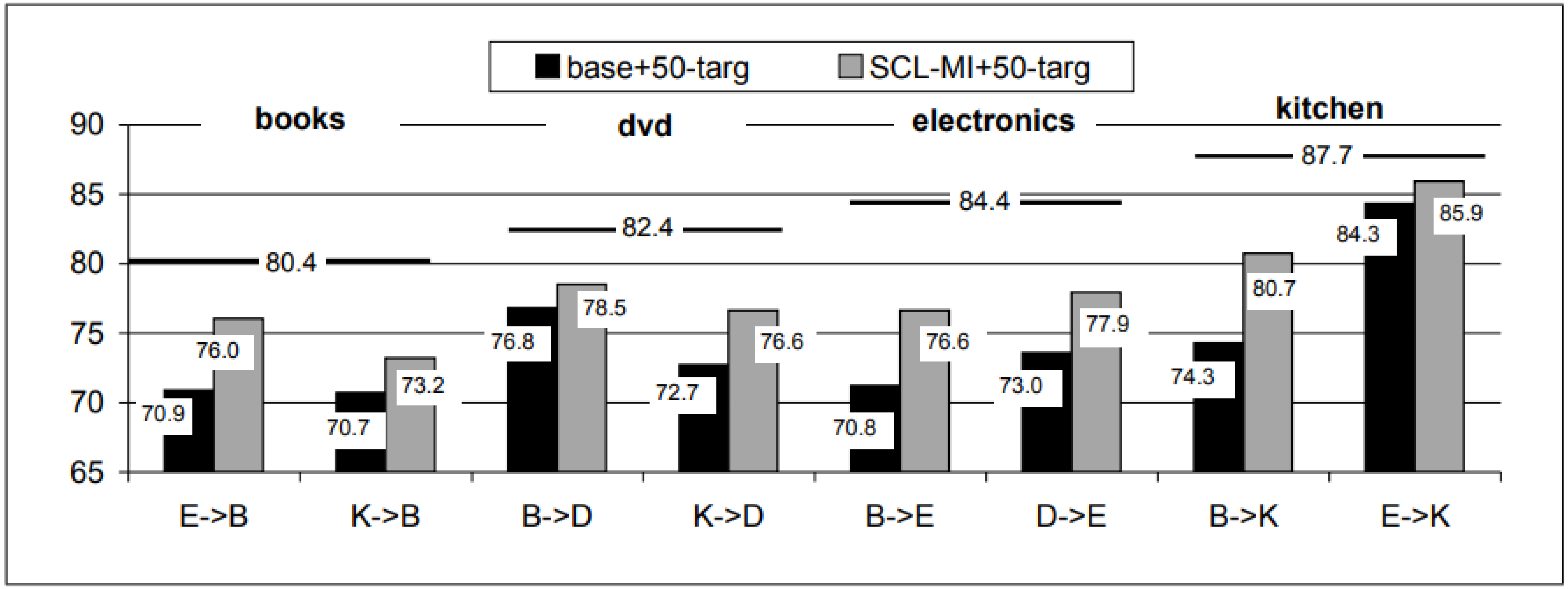



Figure 2: Accuracy results for domain adaptation with 50 labeled target domain instances.

Blitzer et al. 2007

# On Positivity Bias in Negative Reviews

## Core Question:

How are positive words used within negative reviews?

> "Food was ok…***not*** the money they charge. I was *unimpressed* will ***not*** return. I was excited to try this place and was so *disappointed* as my expectations were high. Service ***not*** great and the parking is *awful*."

Aithal & Tan et al. 2021

# Dataset Analysis

Negative reviews have more positive words than negative words

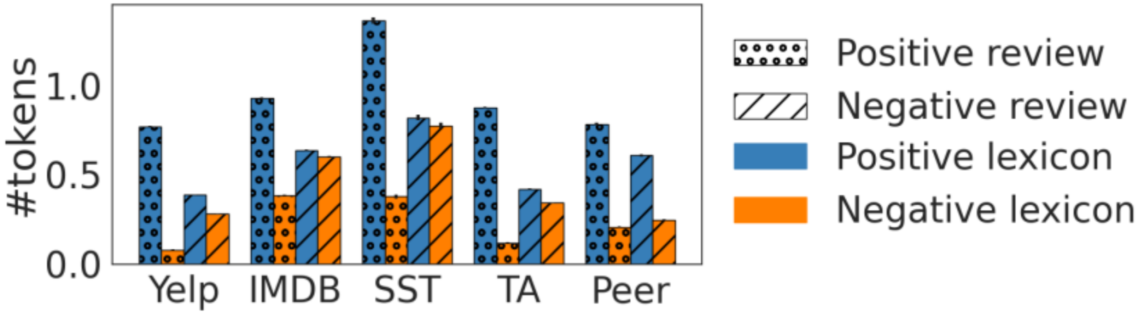



Figure 2: Number of positive and negative words based on Vader. Negative reviews have more positive words than negative words.

Aithal & Tan et al. 2021

# Dataset Analysis

| Dataset | Positive words associated with negations |
|---|---|
| Yelp | recommend, sure, like, good, care, great, special, impressed, fresh, help, ready, enjoy, friendly, honor, helpful, clean, happy, accept, greeted, amazing |
| IMDB | like, care, funny, help, sure, recommend, good, save, fit, great, special, interesting, enjoy, well, play, better, giving, original, convincing, true |
| PeerRead | clear, sure, convincing, convinced, ready, well, true, clearly, surprising, novel, convincingly, recommend, guarantee, improve, interesting, support, satisfactory, help, acceptable, convince |

Table 2: Most frequent positive words that immediately follow negations in negative reviews, based on Vader.

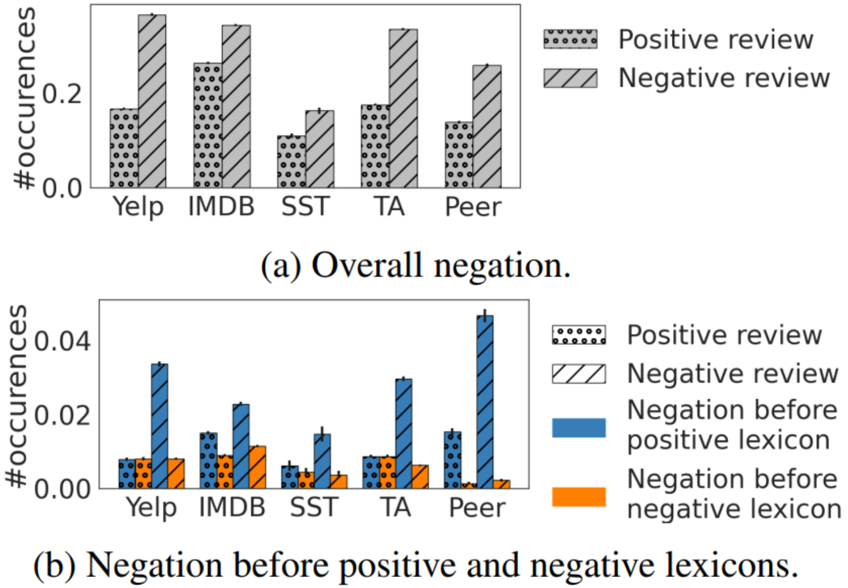
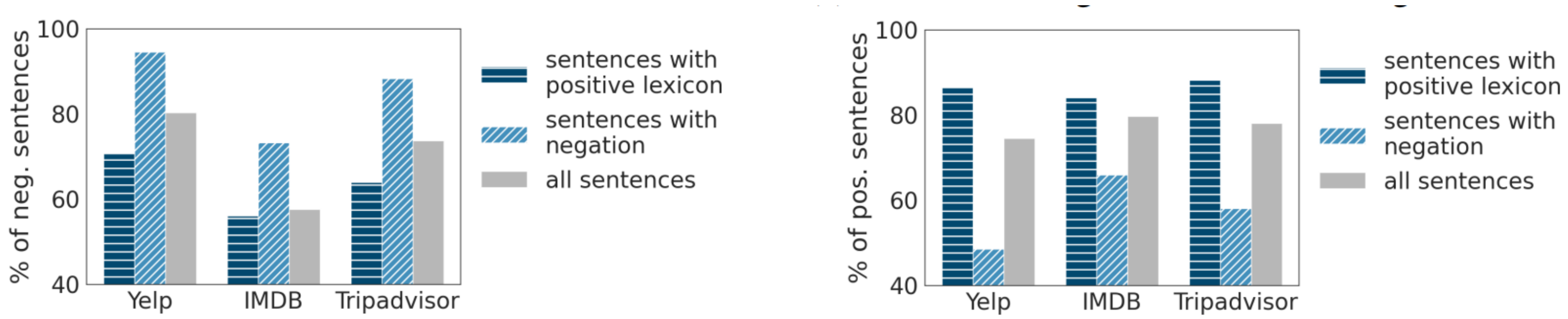



Figure 3: Negative reviews generally have more negations at the sentence level (Figure 3a). Among those negations, Figure 3b shows that there are substantially more negations before positive lexicons in negative reviews than any other combinations.

Aithal & Tan et al. 2021

# Sentence analysis using classification




(a) Fractions of negative sentences in negative reviews. (b) Fractions of positive sentences in positive reviews.

Figure 4: Sentence-level prediction results based on fine-tuned BERT classifiers. In negative reviews, sentences with positive words tend to be negative, and sentences with negations are overwhelmingly negative. In comparison, sentences with negations are more balanced (44.7% negative) in positive reviews.

Aithal & Tan et al. 2021

# #SupportTheCause: Identifying Motivations to Participate in Online Health Campaigns

Core Question:

How does participant motivation *impact* the amount of campaign donations raised?

Nguyen et al. 2015

# Dataset

**Movember Profiles**

- US & UK Movember participants
- Collected May 2015
- 166,222  US and 138,546 UK profiles

**Twitter Data**

- Link Movember participants with Twitter accounts using tweets that link to a Movember profile in 2013 or 2014
- Match 5,519 users
- Collect tweets from 10/18 to 12/14 (two weeks before & after campaign)

Nguyen et al. 2015

# Annotation

Labels based on the Social Identity Model of Collective Action:

- Injustice
  *'my dad', 'I had testicular cancer', 'b/c men's health is important to me'*
- Social Identity
  *'my friends asked me to join', 'a great excuse to grow a stache'*
- Collective Efficacy
  *'this campaign can make a difference!'*

| | Train | Test |
|---|---|---|
| **# Participants** | 1,494 | 614 |
| **% US / UK** | 54.8/45.2 | 53.3/46.7 |
| **% Injustice** | 37.6 | 40.2 |
| **% Social identity** | 48.7 | 46.9 |
| **% Collective efficacy** | 36.1 | 35.0 |

Table 2: Dataset statistics

Nguyen et al. 2015

# Results

Classifiers trained on Movember profiles are fairly accurate

| Features | Injustice | | | | Social Identity | | | | Collective Efficacy | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **P** | **R** | **$F_1$** | **AUC** | **P** | **R** | **$F_1$** | **AUC** | **P** | **R** | **$F_1$** | **AUC** |
| Tokens | 0.813 | 0.789 | 0.801 | 0.833 | 0.768 | 0.792 | 0.779 | 0.790 | 0.595 | 0.656 | 0.624 | 0.708 |
| LDA | 0.789 | 0.802 | 0.795 | 0.829 | **0.809** | 0.795 | **0.802** | **0.815** | 0.514 | **0.688** | 0.588 | 0.669 |
| Length | 0.644 | 0.615 | 0.629 | 0.693 | 0.526 | 0.632 | 0.574 | 0.564 | 0.419 | 0.642 | 0.507 | 0.582 |
| Country | 0.422 | 0.559 | 0.481 | 0.522 | 0.495 | 0.493 | 0.494 | 0.524 | 0.373 | 0.498 | 0.426 | 0.523 |
| All | **0.823** | **0.810** | **0.816** | **0.846** | 0.777 | **0.799** | 0.788 | 0.798 | **0.597** | 0.660 | **0.627** | **0.710** |

Table 1: Results free-text motivations: precision (P), recall (R), $F_1$ score and AUC.

Nguyen et al. 2015

# Results

It's difficult to predict motivation from tweets

| Features | Injustice | | | | Social Identity | | | | Collective Efficacy | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | P | R | $F_1$ | AUC | P | R | $F_1$ | AUC | P | R | $F_1$ | AUC |
| 1: Tokens | 0.456 | 0.445 | 0.451 | 0.544 | **0.528** | 0.563 | 0.545 | **0.559** | **0.394** | 0.465 | 0.426 | **0.540** |
| 2: URLs | 0.421 | 0.304 | 0.353 | 0.511 | 0.469 | **0.736** | **0.573** | 0.500 | 0.360 | 0.209 | 0.265 | 0.504 |
| 3: Mentions | 0.435 | 0.340 | 0.382 | 0.522 | 0.477 | 0.694 | 0.566 | 0.511 | 0.360 | **0.721** | **0.480** | 0.515 |
| 4: Effort | 0.434 | 0.518 | **0.472** | 0.532 | 0.489 | 0.531 | 0.509 | 0.520 | 0.363 | 0.498 | 0.420 | 0.513 |
| 5: LDA | 0.427 | 0.510 | 0.465 | 0.525 | 0.512 | 0.538 | 0.525 | 0.542 | 0.378 | 0.521 | 0.438 | 0.530 |
| 6: Behavior | 0.415 | **0.526** | 0.464 | 0.514 | 0.463 | 0.410 | 0.435 | 0.495 | 0.360 | 0.581 | 0.445 | 0.513 |
| 1+3+4+5+cntry | **0.463** | 0.453 | 0.458 | **0.550** | 0.520 | 0.542 | 0.531 | 0.550 | 0.381 | 0.419 | 0.399 | 0.526 |

Table 3: Results on tweets: precision (P), recall (R), $F_1$ score and AUC.

Nguyen et al. 2015

# Motivations & Campaign Behavior

| | % Injustice | % Identity | % Efficacy |
|---|---|---|---|
| UK | 31.0 | 49.7 | 46.1 |
| US | 37.6 | 50.3 | 32.1 |

Table 5: Motivation distribution based on automatic annotation (n=90,484). Note that participants may have multiple motivations.

| | Injustice | Identity | Efficacy |
|---|---|---|---|
| UK ($) | 203.74 | 128.36 | 123.39 |
| US ($) | 234.47 | 156.07 | 169.03 |

Table 6: Average amount raised (n=90,484). British pounds were converted in dollars following the exchange rate in November 2013.

Nguyen et al. 2015

# How Did This Get Funded?!

## Automatically Identifying Quirky Scientific Achievements

Core Question:

Can we automatically detect funny and unusual scientific papers?

Shani et al. 2021

# Dataset

**Scientific Paper Titles**

- 1707 humorous papers
  - 211 Ig Nobel winners
  - Others manually collected from online forums and blogs
- 1707 randomly sampled papers
  - Fields: neuroscience, medicine, biology, exact sciences
  - Select to preserve field balance

**Binary Labels**

Is this paper title humorous / “Ig Nobel worthy”?

Shani et al. 2021

# Classification

Feature Categories:

- Unexpected Language
- Simple Language
- Crude Language
- Funny Language

| Model | Accuracy | Precision | Recall |
|---|---|---|---|
| Iggy | 0.897 | 0.901 | 0.893 |
| SciBERT | 0.910 | 0.911 | 0.911 |
| SciBERT$^f$ | **0.922** | **0.919** | **0.926** |
| BERT | 0.904 | 0.906 | 0.893 |
| BERT$^f$ | 0.900 | 0.899 | 0.902 |
| RF | 0.761 | 0.746 | 0.796 |
| LR | 0.781 | 0.754 | 0.837 |

Table 2: Accuracy of the different models on our dataset using cross validation with k=5. SciBERT$^f$ outperforms.

Shani et al. 2021

# Evaluating “in the Wild”

| Title | Models |
|---|---|
| The kinematics of eating with a spoon: Bringing the food to the mouth, or the mouth to the food? | Iggy, BERT$^f$, SciBERT$^f$ |
| Do bonobos say NO by shaking their head? | Iggy, BERT$^f$, SciBERT$^f$ |
| Is Anakin Skywalker suffering from borderline personality disorder? | Iggy, BERT$^f$, SciBERT$^f$ |
| Not eating like a pig: European wild boar wash their food | Iggy, BERT$^f$ |
| Why don’t chimpanzees in Gabon crack nuts? | SciBERT$^f$, BERT$^f$ |
| Why do people lie online? “Because everyone lies on the internet” | BERT$^f$ |
| Which type of alcohol is easier on the gut? | BERT$^f$ |
| Rainbow connection and forbidden subgraphs | BERT |
| A scandal of invisibility: making everyone count by counting everyone | SciBERT |
| Where do we look when we walk on stairs? Gaze behaviour on stairs, transitions, and handrails | SciBERT |

Table 4: A sample of top rated papers found by our models.

Shani et al. 2021

# Unravelling Names of Fictional Characters

Core Question:

Can the polarity of a character's role be predicted by their name alone?

Papantoniou et al. 2016

# Kevinism

"Kevin isn't a name, but a diagnosis"

*"Kevin ist kein Name, sondern eine Diagnose"*

Trenkamp 2009

# Dataset

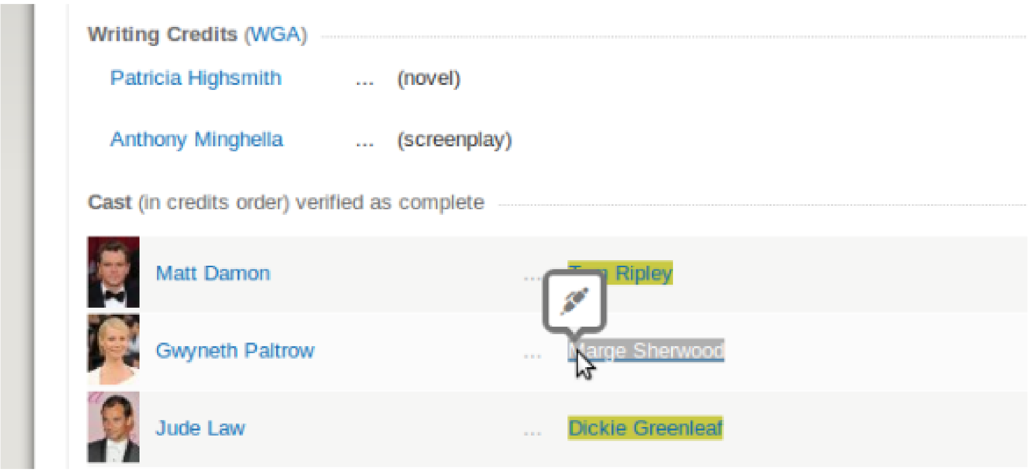



Figure 1: Character annotation tool

- Positive: the role of the character in the plot left a positive impression
- Negative: the role of a character left a negative impression
- *Neutral: ignored label*

Papantoniou et al. 2016

# Results

| | Rec. | Prec. | F-score |
|---|---|---|---|
| Without domain features | 0.803 | 0.801 | 0.802 |
| Only domain features | 0.725 | 0.699 | 0.667 |
| Only phonological features | 0.790 | 0.786 | 0.787 |
| Without poetic features | 0.836 | 0.832 | 0.833 |
| Without consonance feature | 0.823 | 0.820 | 0.821 |
| Without emotions features | 0.814 | 0.810 | 0.811 |
| Without phonological features | 0.798 | 0.792 | 0.793 |
| Without social features | 0.807 | 0.803 | 0.804 |
| All features | 0.824 | 0.822 | 0.823 |

Table 5: Performance of J48 for different feature settings

Papantoniou et al. 2016

# Feature Analysis

| Phonemes | Class |
|---|---|
| /p/, /b/ (bilabial plosive) | P |
| /l/ (alveolar lateral) | P |
| /f/, /v/ (labiodental africative) | N |
| /k/, /g/ (velar plosive) | N |
| /t/, /d/ (alveolar plosive) | N |
| /dʒ/, /tʃ/ (affricate) | N |
| /m/, /n/ (nasal) | N |
| /ɹ/ (alveolar retroflex) | N |

Table 7: Consonants behavior

| Most frequent in positive characters | |
|---|---|
| Phoneme n-gram | Examples |
| /lɪ/ | Ned Alleyn (Shakespeare in Love) |
| /an/ | Anouk Rocher (Chocolat) |
| /aɪ/ | Eliza Doolittle (My Fair Lady) |
| /nɪ/ | Linguini (Ratatouille) |
| /ɪst/ | Kevin McCallister (Home Alone) |
| /ɹəʊ/ | Frodo (The Lord of the Rings) |
| /and/ | Dylan Sanders (Charlie's Angels) |
| /stə/ | C.C. Baxter (The Apartment) |
| **Most frequent in negative characters** | |
| Phoneme n-gram | Examples |
| /ən/ | Tom Buchanan (The Great Gatsby) |
| /əʊ/ | Iago (Aladdin) |
| /tə/ | Norrington (Pirates of the Caribbean) |
| /ɹɪ/ | Tom Ripley (The Talented Mr. Ripley) |
| /mən/ | Norman Bates (Psycho) |
| /mɪs/ | Mystique (X-Men) |
| /ktə/ | Hannibal Lecter (Hannibal) |

Table 6: Frequent phoneme {2,3}-grams

Papantoniou et al. 2016