# Abusive behavior in social media

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# Outline

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- Problem definition
- Challenges
- Solution approaches

## Abusive Yahoo! comments

## Agressive Twitter accounts

## Conclusion

# Abusive behavior

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## Types

- Frequency (aggressive behavior ↔ bullying)
- Channel (physical, verbal, relational, property)

## Offline

- All of the above

# Abusive behavior

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## Online

- Pysical ✗
- Property ?
- Relational ✓
- Verbal ✓

# Abusive behavior

## Types

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## Offline

- All of the above

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- Pysical
- Property
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- Verbal ⬅

# Problem definition

## General

- detect (stop) abusive behavior
- here “behavior” = textual communication

## Operator’s perspective

- available information
    - actor (≈real person/consistent ↔ anonymous)
- problem modeling
    - abusive user
    - abusive content

# **Problem definition** | Examples

**Facebook**

- user ≈ real person
- friends
- likes
- activity patterns
- (→ qualities of user that engages in abusive behavior)

**4chan**

- consistency throughout one session
- … maybe
- (→ abusive content)

# Challenges

## User

- intentional obfuscation
- sarcasm
  - false positives
  - bullying

## Language

- multi sentence
- social context
- language changes

# **Challenges** | Examples

## Intentional obfuscation

- $hit
- SHІT

  ↰ cyrillic capital letter byelorussian-ukrainian i (U+0406)
- sh‌it

  ↰ zero width non-joiner (U+200C)

# **Challenges** | Examples

**Sarcasm**

- false positives:
  “oh of course we should kill them all that would clearly solve all the problems.”

- bullying:
  “what a genius idea!”
  “who would’ve thought of that? amazing!”
  “damn you’re smart!”
  “you REALLY know what you’re talking about!”
  …

# **Challenges** | Examples

### Multi sentence

- “I tell you the [ethnic group] are the reason. We’d better get rid of them all.”

### Social context

- utterance X
  - acceptable to group A
  - not acceptable to group B

### Language changes

- offensive words loose their impact over time
  → new offensive words

# Solution approaches

### Word lists

- ✗ blacklists
- ✓ features

### n-grams

- example: 3-grams → exa, xam, amp, mpl, ple
- padded: $$p, $pa, pad, add, dde, ded, ed$, d$$
- level: character / token

# Solution approaches

## tf-idf

- word importance
- $\#\text{term}|_{\text{Doc}} \cdot \log \dfrac{\#\text{Doc}}{\#\text{Doc}|_{\text{contains term}}}$

## POS tags

- word-category disambiguation
  - noun
  - verb
  - preposition

→ similarity

# Solution approaches

**Domain specific**

- URLs
- hashtags
- CAPS
- mentions
- emojis
- etc.

→ similarity

# Solution approaches

## Distributional semantics

- word embeddings
  - “the ice cream melted quickly” 0 1 0 0 0
  - “the ice cream melted quickly” 1 0 1 1 1
- word2vec: king – man + woman = queen

## Inter word dependencies

- “[ethnic group] are lower class pigs”

→ context

# Solution approaches

**Beyond just text**

- user
  - likes
  - activity patterns
  - profile (picture, age, ...)
- network
  - centrality
  - polularity
  - reciprocity
- ... if possible

# Two concrete approaches

## Targets

- Abusive Yahoo! comments [1]
- Aggressive Twitter accounts [2]

## Discussion

- Data
- Features
- Experiments

[1] C. Nobata, J. Tetreault, A. Thomas, Y. Mehdad, and Y. Chang.
Abusive language detection in online user content.
WWW '16, pages 145–153, 2016.

[2] D. Chatzakou, N. Kourtellis, J. Blackburn, E. D. Cristofaro, G. Stringhini, and A. Vakali.
Mean birds: Detecting aggression and bullying on twitter.
CoRR, abs/1702.06877, 2017.

# Two concrete approaches

**Targets**

- Abusive Yahoo! comments [1]
  - abusive content
- Aggressive Twitter accounts [2]
  - abusive users

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# Abusive Yahoo! comments

**Detect**

- hate speech
- derogatory language
- profanity

**In**

- Comments
  - Yahoo! News
  - Yahoo! Finance

# Abusive Yahoo! comments | Data

| **Data sets** | % abusive | |
|---|---|---|
| • primary (2.1 M) | 13 | |
| • temporal (1.2 M) | 7 | |
| • WWW15 (1 M) | 6 | |
| • evaluation (2 K) | 50 | (tripple labels) |

**Labels**

- Yahoo! employees
- Amazon Mechanical Turk*

# Abusive Yahoo! comments | Features

**Features**

- n-grams
- syntactic
- linguistic
- distributional semantics

# Abusive Yahoo! comments | Features

**Features**

- n-grams
- syntactic
- linguistic
- distributional semantics

**Syntactic**

- inter word dependencies, POS tags

**Linguistic**

- average word length, number of CAPS, URLS, tokens, punctuations, hate speech words, ...

# **Abusive Yahoo! comments** | Experiments

| **Primary data set** | F-scores | |
|---|---|---|
| all features: | 0.80 | 0.82 |
| token n-grams: | 0.77 | 0.74 |
| char. n-grams: | 0.73 | 0.77 |

**Goal and interpretation**

- assess feature contribution (only highlights shown above)
- n-grams alone give high quality results

# Abusive Yahoo! comments | Experiments

## WWW15 dataset

| | | |
|---|---|---|
| F-score: | 0.78 | - |
| AUC now: | 0.90 | |
| AUC ‘15: | 0.80 | |

## Goal and interpretation

- outperforms approach from 2015 [3]

[3] N. Djuric, J. Zhou, R. Morris, M. Grbovic, V. Radosavljevic, and N. Bhamidipati.
Hate speech detection with comment embeddings.
WWW ‘15, 2015.

# Abusive Yahoo! comments | Experiments

## Evaluation dataset

- F-score all agree: 0.84
- majority: 0.83
- 2 of 3: 0.43

## Goal and interpretation

- test ground truth (calculation) variations
- lanugage is hard to judge

# Abusive Yahoo! comments | Experiments

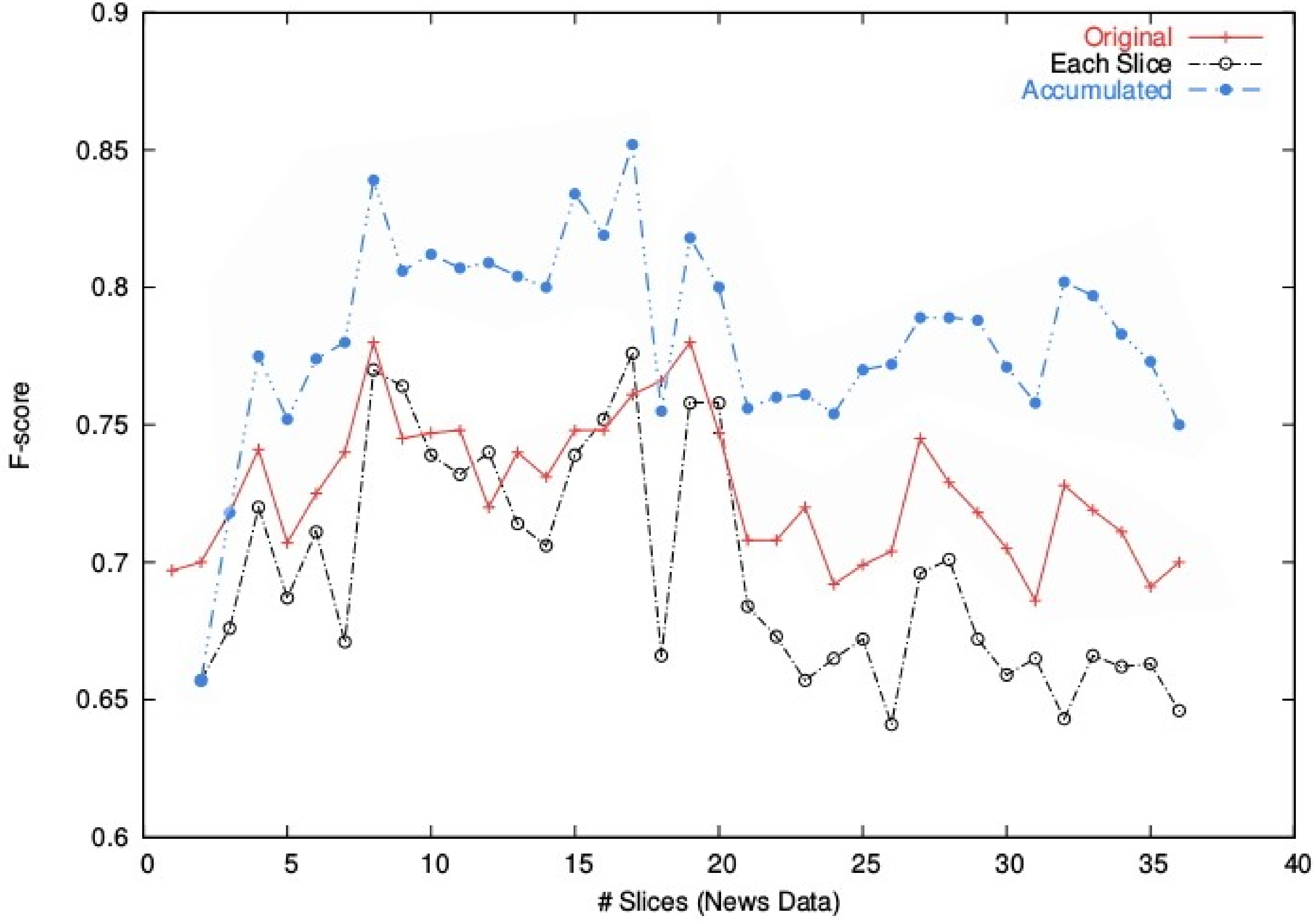
## Temporal data set

| | | |
|---|---|---|
| • Original | train(primary) | predict(t) |
| • Each slice | train(t) | predict(t+1) |
| • Accumulated | train(0..t) | preditct(t+1) |

## Goal

- assess how much training data is necessary
- assess if updating a model is necessary

# **Abusive Yahoo! comments** | Experiments



# Abusive Yahoo! comments | Experiments

## Temporal data set

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## Interpretation

- Each slice close to Original
  → reasonable predictions for small training data
- Accumulated best
  → recent training data more important than much

# Aggressive Twitter accounts

**Detect**

- bullying
- aggressive behaviour

**In**

- Twitter accounts
    - Tweets
    - profile

# Aggressive Twitter accounts | Data

## Data sets

- baseline (1 M)
- hate related (650 K)
  - #GamerGate

## Labels

- CrowdFlower
- fivefold, majority
- → 9,484 annotated
  - 60% normal
  - 32% spam
  - 4.5% bully
  - 3.5% aggressive

# Aggressive Twitter accounts | Features

## User

- account age, verified,
  interarrival time, num. tweets,
  session statistics

## Text

- num. hashtags, emoticons, URLs,
  hate score, word embeddings

## Network

- num. friends, followers, polularity (fo/fr),
  reciprocity, centrality scores

# **Aggressive Twitter accounts** | Experiments

## Features

- 12 not useful
  - (session stats, hate score, word embeddings, etc.)

## Classification

- 4-classes: bully, aggressive, normal, spam
- 3-classes: bully, aggressive, normal

# Aggressive Twitter accounts | Experiments

**Features**

- 12 not useful
  - (session stats, hate score, word embeddings, etc.)

| **Classification** | precision | recall | (in %) |
|---|---|---|---|
| - 4-classes: | 72 | 73 | |
| - 3-classes: | 90 | 92 | |

**Interpretation**

- actual textual content comparably not very useful
- approach works well

# Conclusion

## Central differences

- abusive content vs. behavior
- target: comments vs. users

## Take-home messages

- natural language is hard
- context is valuable

- what about other languages?
- what about non-textual abusive behavior?

# Discussion & Questions

”Participation in discussions [...] is also part of the final grade assigned”

(no pressure)

# Sources

- C. Nobata, J. Tetreault, A. Thomas, Y. Mehdad, Y. Chang.
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  *Hate speech detection with comment embeddings*.
  WWW ‘15, 2015.
- V. Le Quoc, T. Mikolov
  *Distributed Representations of Sentences and Documents*.
  CoRR, abs/1405.4053, 2014.