


Hate Speech Detection is Not as Easy as You May Think: A Closer Look at Model Validation

Aymé Arango, Jorge Pérez and Bárbara Poblete





**ALMOST PERFECT
STATE-OF-THE-ART
RESULTS**

VS



**UNDETECTED
HATE SPEECH
IN
SOCIAL MEDIA**

Bloomberg

Twitter Apologizes for Ignoring Bomb Suspect's Apparent Threat in Tweet

October 27, 2018, 12:04 AM GMT-3 Updated on October 27, 2018, 1:20 AM GMT-3

NEWS | RACIAL JUSTICE

Civil Rights Groups Have Been Warning Facebook About Hate Speech for Years

EdSurge

Twitter Is Funding Research Into Online Civility. Here's How One Project Will Work.

By Jeffrey R. Young Aug 14, 2018



THE UNIVERSITY OF
SYDNEY

University researchers to help Facebook counter hate speech

30 May 2019

UNDETECTED
HATE SPEECH
IN
SOCIAL MEDIA

**ALMOST PERFECT
STATE-OF-THE-ART
RESULTS**

94% F1
[Agrawal and Awekar]
ECIR
2018

93% F1
[Badjatiya et al.]
WWW
2017

92% F1
[Zeeraq Waseem]
NAACL
2016

Hate Speech Detection is Not as Easy as You May Think

We show that state of the art results are highly overestimated due to experimental issues in the models:

Including the testing set during training phase

Oversampling the data before splitting

User-biased datasets

State-of-the-art replication

User distribution

Generalization

State-of-the-art replication

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**ALMOST PERFECT
STATE-OF-THE-ART
RESULTS**

94% F1
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WWW
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2016

DATASET 1
[Waseem and Hovy]
NAACL
2016

Tweet

Label



This is a hateful tweet!!


Hate

 Traducir Tweet

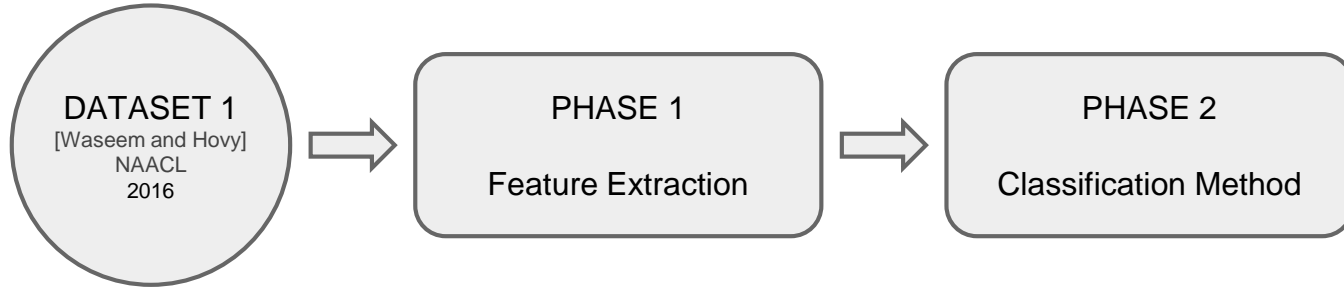


This is a normal tweet

Non-Hate

 Traducir Tweet

Model 1
[Badjatiya et al.]
2017



93% F1

PHASE 1
Feature Extraction

DATASET 1
[Waseem and Hovy]
NAACL
2016

Embeddings

LSTM

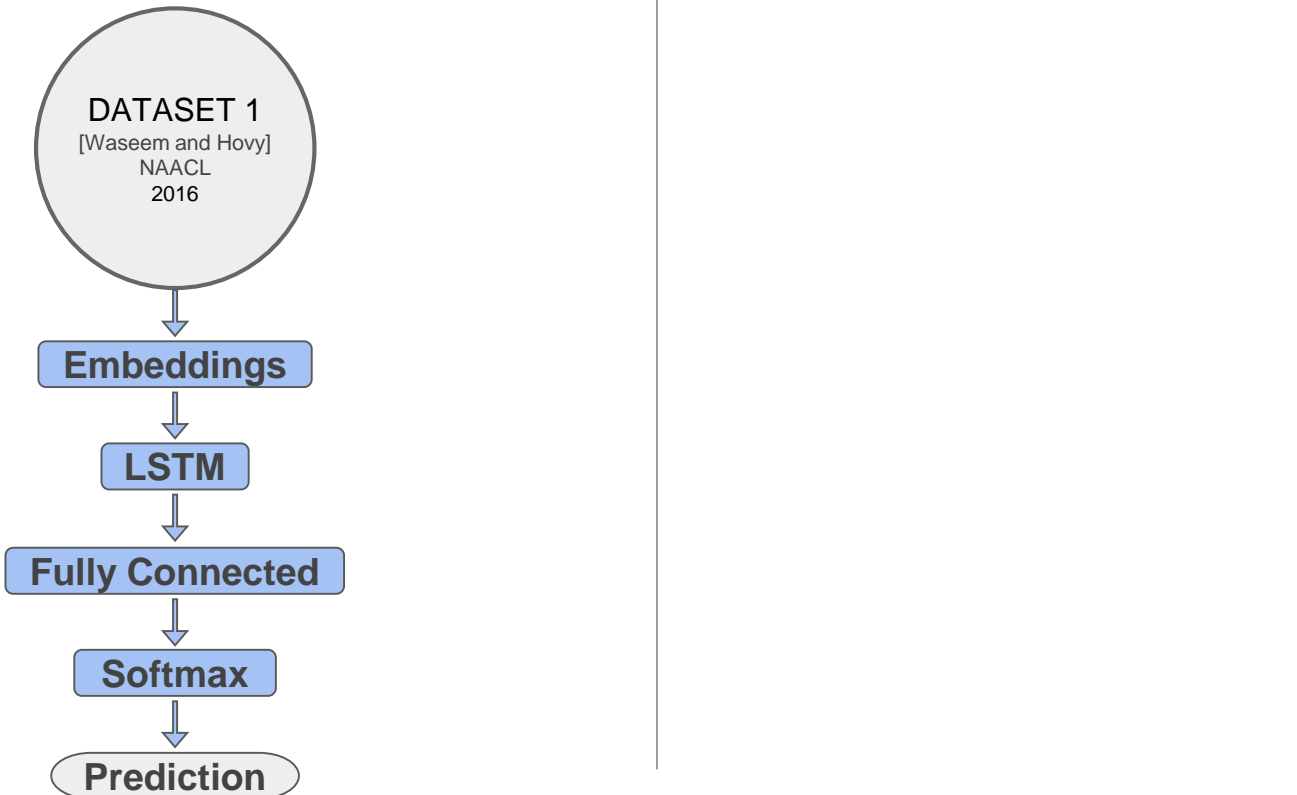
Fully Connected

Softmax

Prediction

Model 1
[Badjatiya et al.]
2017

PHASE 2
Classification Method



PHASE 1
Feature Extraction

DATASET 1
[Waseem and Hovy]
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NAACL
2016

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Model 1
[Badjatiya et al.]
2017

Splitting



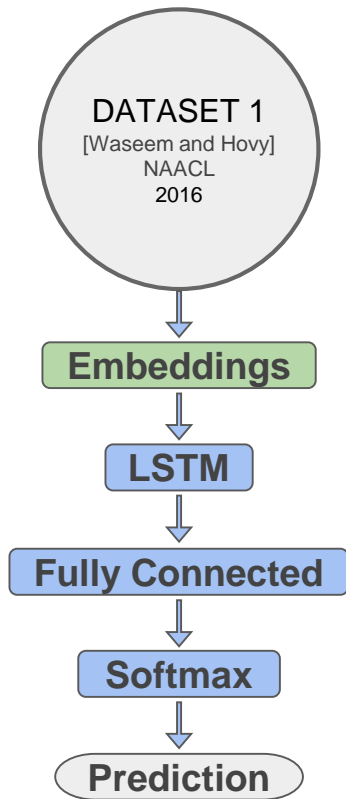
PHASE 2
Classification Method

TRAIN

TEST

Embeddings

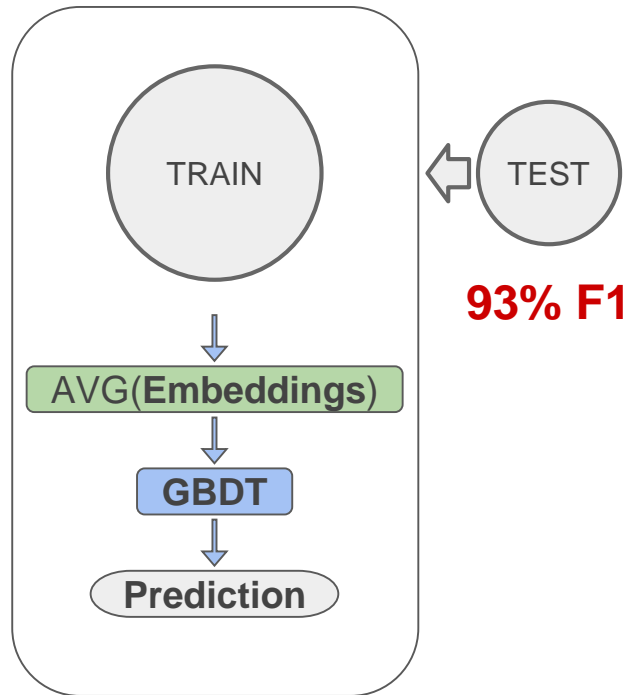
PHASE 1
Feature Extraction



Model 1
[Badjatiya et al.]
2017

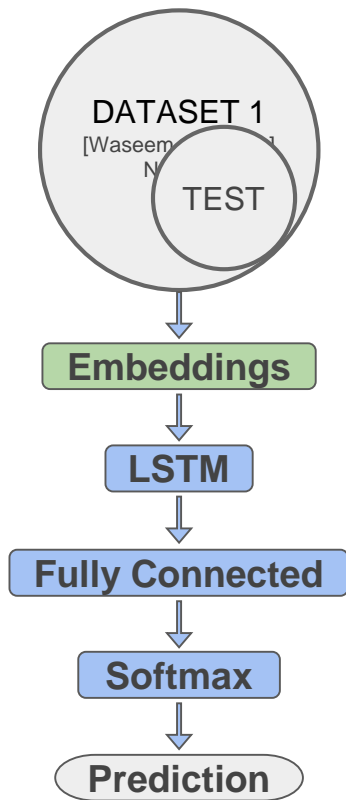


PHASE 2
Classification Method



This looks great! But there is a problem.

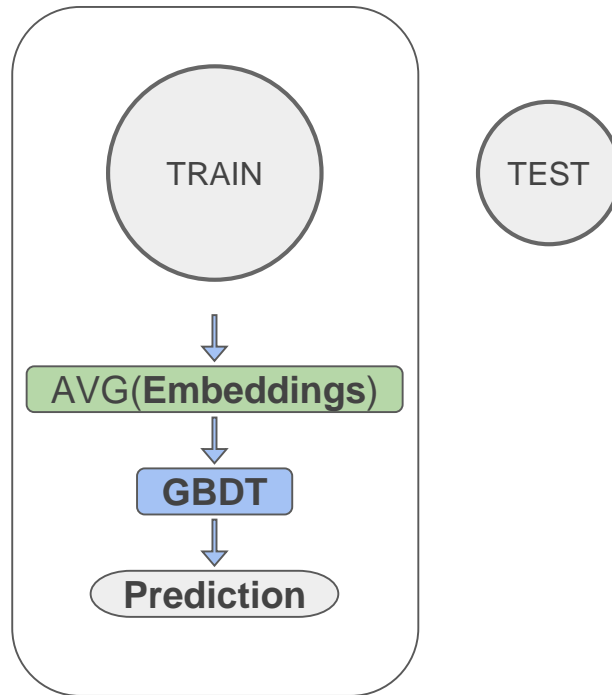
PHASE 1
Feature Extraction



Model 1
[Badjatiya et al.]
2017



PHASE 2
Classification Method



Let's create the model only with the training set.

PHASE 1
Feature Extraction

DATASET 1
[Waseem and Hovy]
NAACL
2016

Model 1
[Badjatiya et al.]
2017

PHASE 2
Classification Method



New PHASE 1
Feature Extraction

TRAIN

TEST

Model 1
[Badjatiya et al.]
2017

Same Splitting

PHASE 2
Classification Method

TRAIN

TEST

New PHASE 1
Feature Extraction

TRAIN

↓
Embeddings

↓
LSTM

↓
Fully Connected

↓
Softmax

↓
Prediction

Model 1
[Badjatiya et al.]
2017

Same Splitting →

PHASE 2
Classification Method

TRAIN

TEST

New PHASE 1
Feature Extraction

TRAIN

↓
Embeddings

↓
LSTM

↓
Fully Connected

↓
Softmax

↓
Prediction

Model 1
[Badjatiya et al.]
2017

Same Splitting →



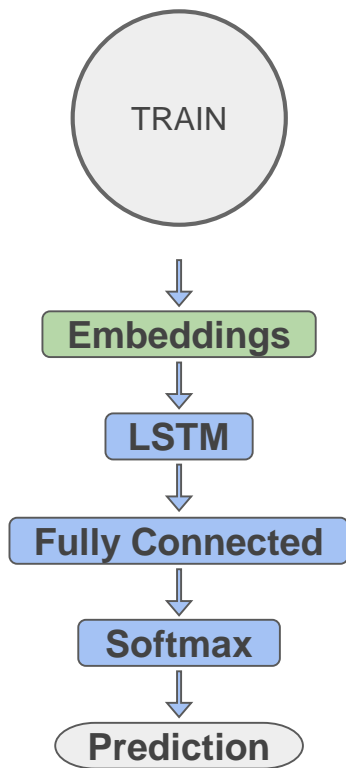
PHASE 2
Classification Method

TRAIN

TEST

Embeddings

New PHASE 1
Feature Extraction

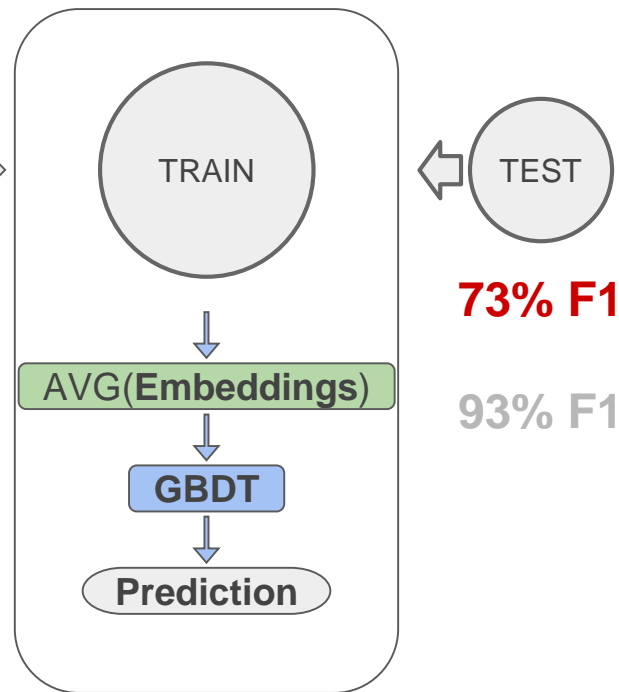


Model 1
[Badjatiya et al.]
2017

Same Splitting

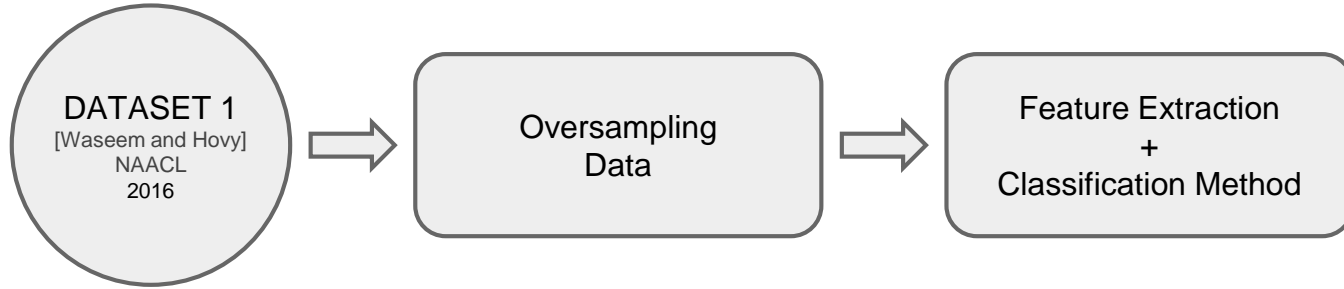


PHASE 2
Classification Method



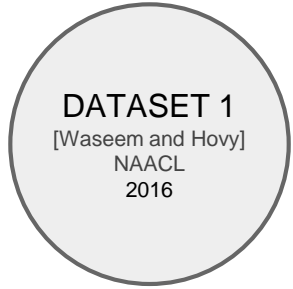
The result is overestimated due to the inclusion of the testing set during the training phase.

Model 2
[Agrawal and Awekar]
2018

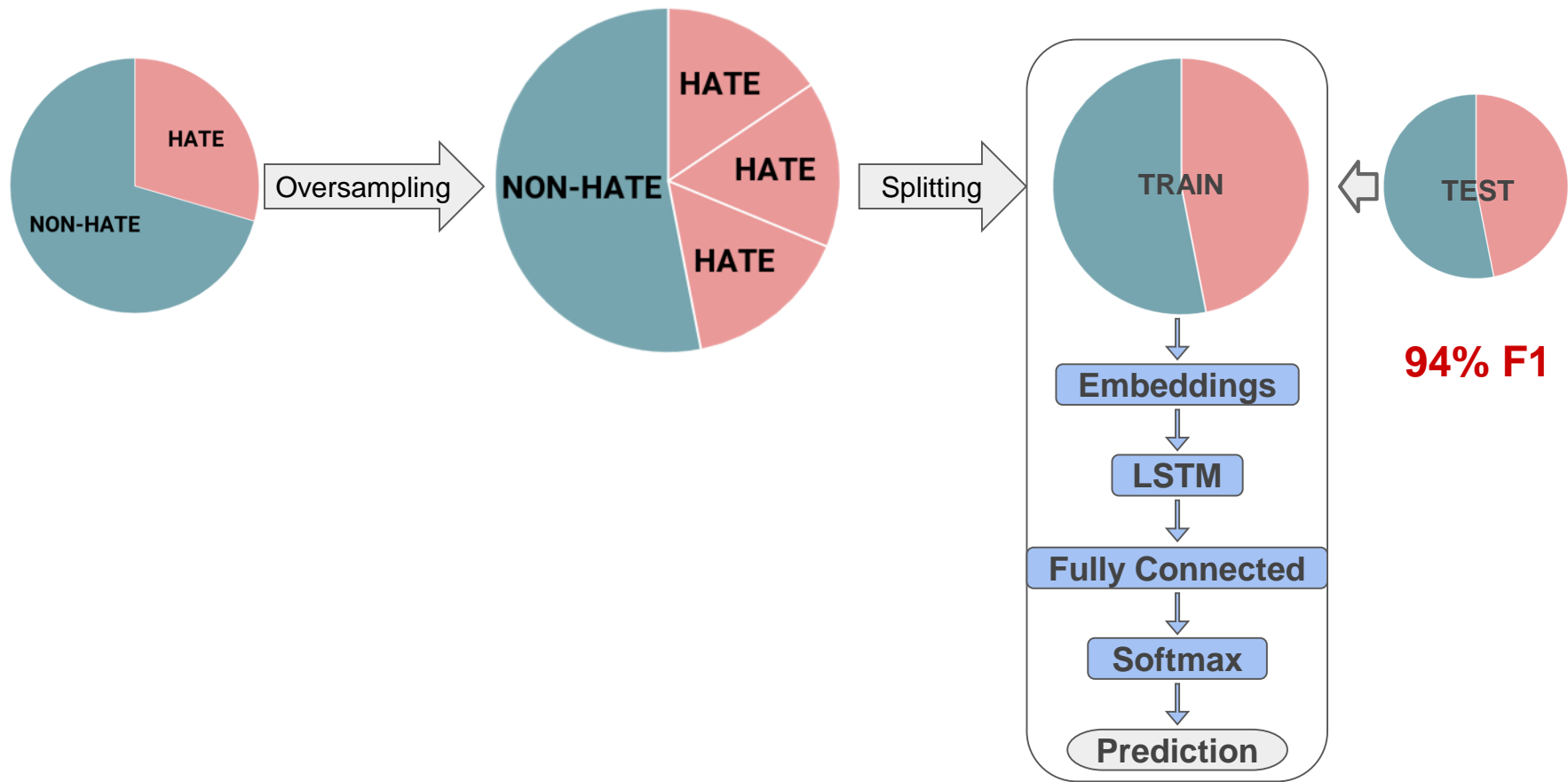


94% F1

Model 2
[Agrawal and Awekar]
2018

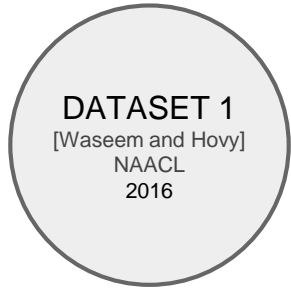


Model 2
[Agrawal and Awekar]
2018

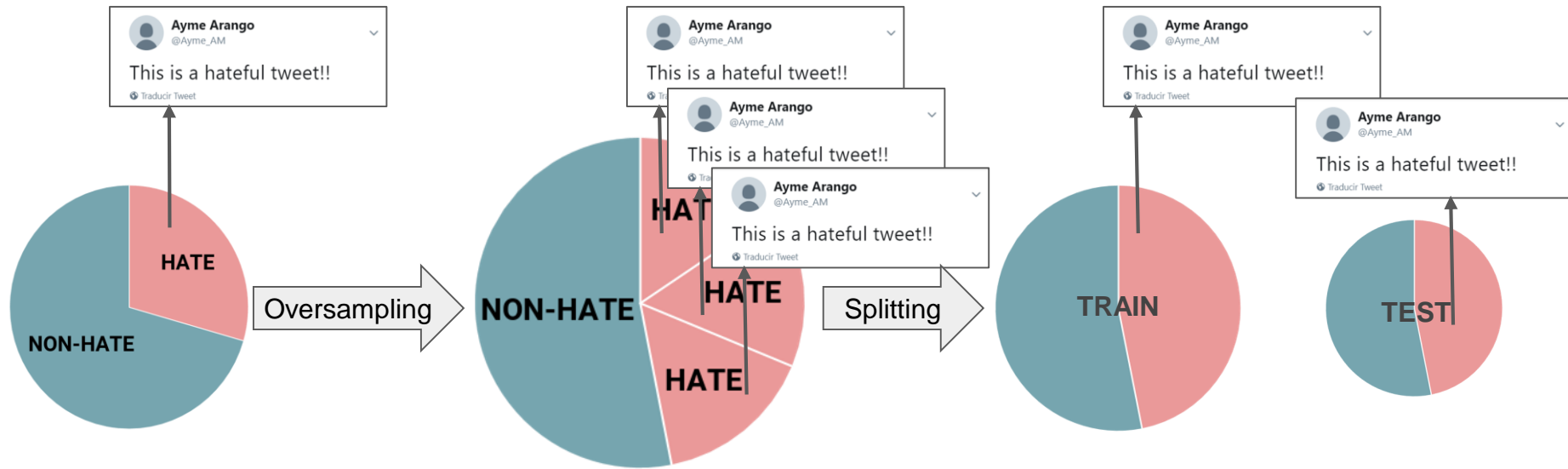


This also looks great! But there is another problem.

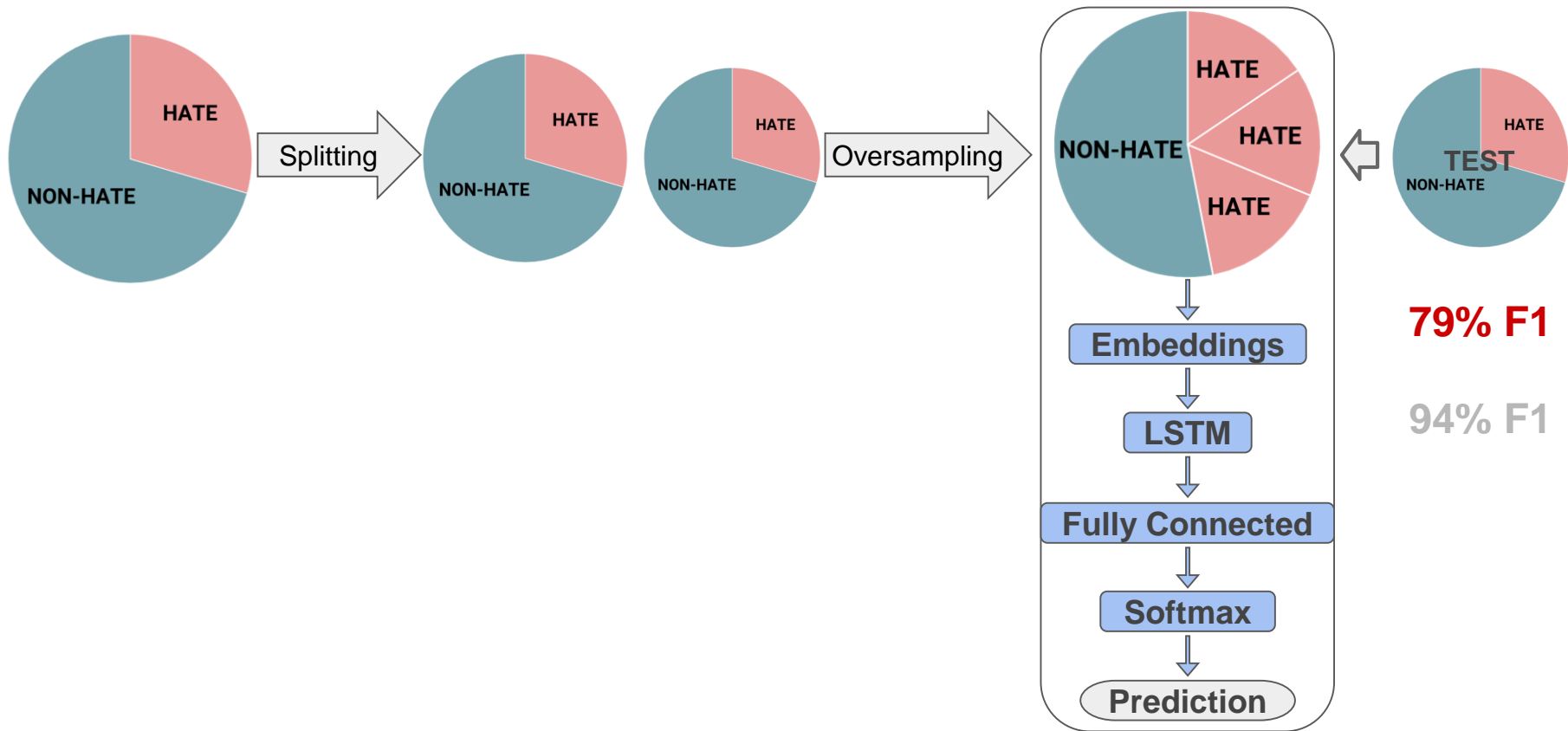
Model 2
[Agrawal and Awekar]
2018



Model 2 [Agrawal and Awekar] 2018



Model 2
[Agrawal and Awekar]
2018



The result is overestimated due to the fact that the oversampling phase occurs before splitting the data.

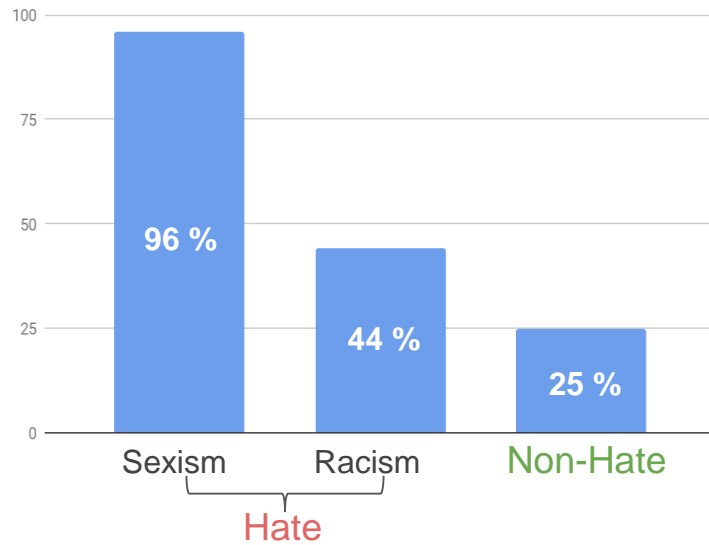
However, there is another issue to take into account.

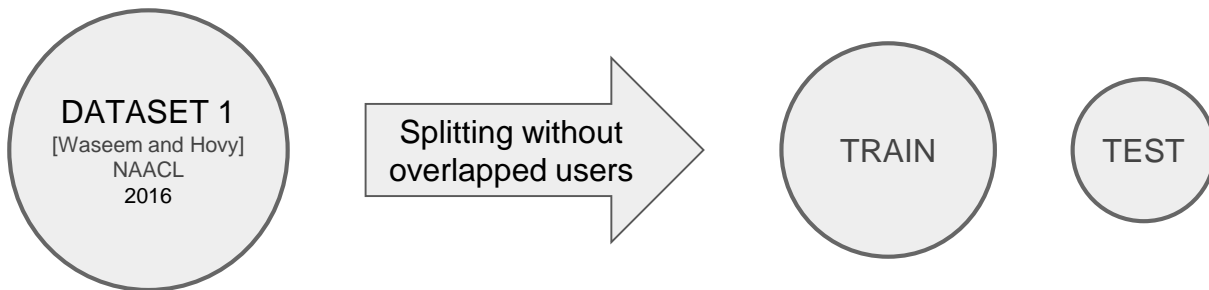
State-of-the-art replication

User distribution

Generalization

% Tweets from the most prolific user per class

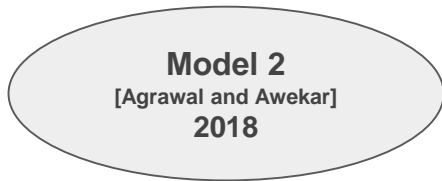




44% F1

73% F1

93% F1

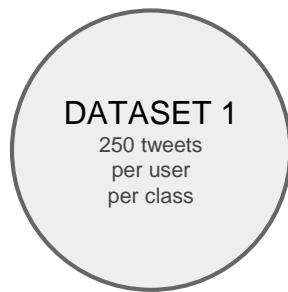


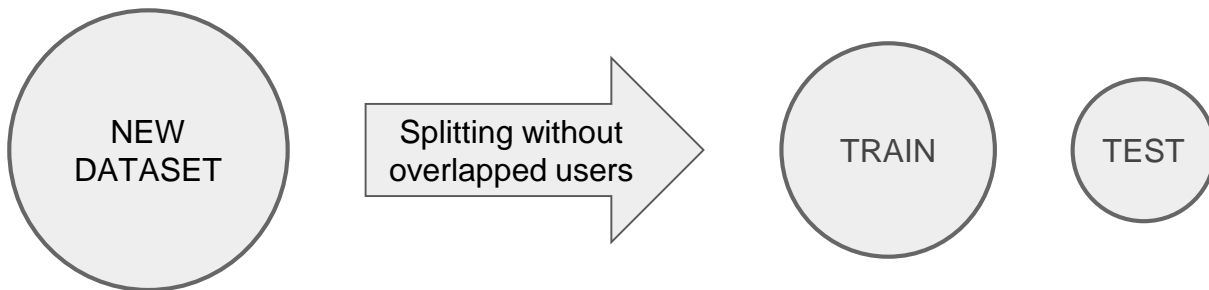
35% F1

79% F1

94% F1

What happens if we have a dataset with a better user distribution?





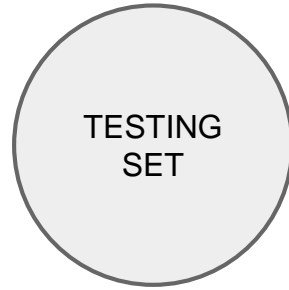
Model 1 [Badjatiya et al.] 2017	78% F1	44% F1	73% F1	93% F1
Model 2 [Agrawal and Awekar] 2018	76% F1	35% F1	79% F1	94% F1

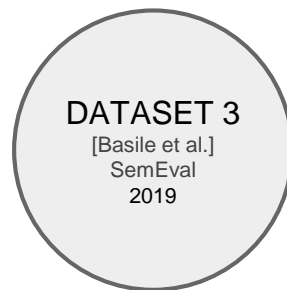
User distribution on datasets has an impact
on the classification results.

State-of-the-art replication

User distribution

Generalization





Model 1
[Badjatiya et al.]
2017

DATASET 1
[Waseem and Hovy]
NAACL
2016

DATASET 3
[Basile et al.]
SemEval
2019

47% F1

**NEW
DATASET**

DATASET 3
[Basile et al.]
SemEval
2019

51% F1

Model 2
[Agrawal and Awekar]
2018

DATASET 1
[Waseem and Hovy]
NAACL
2016

DATASET 3
[Basile et al.]
SemEval
2019

51% F1

**NEW
DATASET**

DATASET 3
[Basile et al.]
SemEval
2019

54% F1

Better user-distributed datasets lead to better generalization.

Conclusions

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