

# Overview of the Celebrity Profiling Task at PAN 2020

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LeFloid 🎤✓  
@LeFloid



Kendall ✓  
@KendallJenner



Neymar Jr. ✓  
@nejmarjr



Lil Wayne WEEZY F ✓  
@LilTunechi

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# Celebrity Profiling

## Motivation

### Celebrity Profiling 2020:

Given the Twitter feeds of the followers of a celebrity, determine the demographics.

# Celebrity Profiling

## Motivation

### Celebrity Profiling 2019:

Given the Twitter feeds ~~of the followers~~ of a celebrity, determine the demographics.

#### Why Celebrities?

- They write many public, high-quality texts.
- Many personal demographics are public knowledge.

# Celebrity Profiling

## Motivation

### Celebrity Profiling 2019:

Given the Twitter feeds ~~of the followers~~ of a celebrity, determine the demographics.

#### Why Celebrities?

- They write many public, high-quality texts.
  - Many personal demographics are public knowledge.
- This is not the case for many users on social media.

# Celebrity Profiling

## Motivation

### Celebrity Profiling 2020:

Given the (?) of a celebrity, determine the demographics.

How can we profile users that do not write a lot?

# Celebrity Profiling

## Motivation

### Celebrity Profiling 2020:

Given the **Twitter profile** of a celebrity, determine the demographics.

How can we profile users that do not write a lot?

- Author Metadata: Biography, profile picture, ...

The image shows a screenshot of Justin Bieber's Twitter profile. At the top, there is a promotional banner for the song "HOLY" featuring Justin Bieber and Chance the Rapper, with the text "Out Now". Below the banner is his profile picture, which is a circular photo of him in a field. His name, "Justin Bieber", is displayed in bold black text with a blue verified checkmark, and his handle "@justinbieber" is shown below it. A bio states "First single...HOLY out now @chancetherapper". Below the bio are links to his website ("JustinBieber.Ink.to/Holy") and his account creation date ("Joined March 2009"). At the bottom, it shows he has 296.3K Following and 112.5M Followers. There are also "Follow" and "More" buttons.

# Celebrity Profiling

## Motivation

### Celebrity Profiling 2020:

Given the **behavior on Twitter** of a celebrity, determine the demographics.

How can we profile users that do not write a lot?

- Author Metadata: Biography, profile picture, ...
- Author Behavior: Retweets, Likes, ...

# Celebrity Profiling

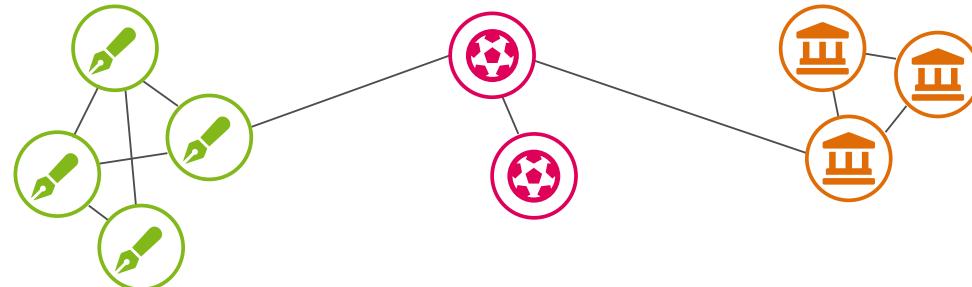
## Motivation

### Celebrity Profiling 2020:

Given the Twitter feeds of the followers of a celebrity, determine the demographics.

How can we profile users that do not write a lot?

- Author Metadata: Biography, profile picture, ...
- Author Behavior: Retweets, Likes, ...
- Social Graph: Homophily.



# Celebrity Profiling

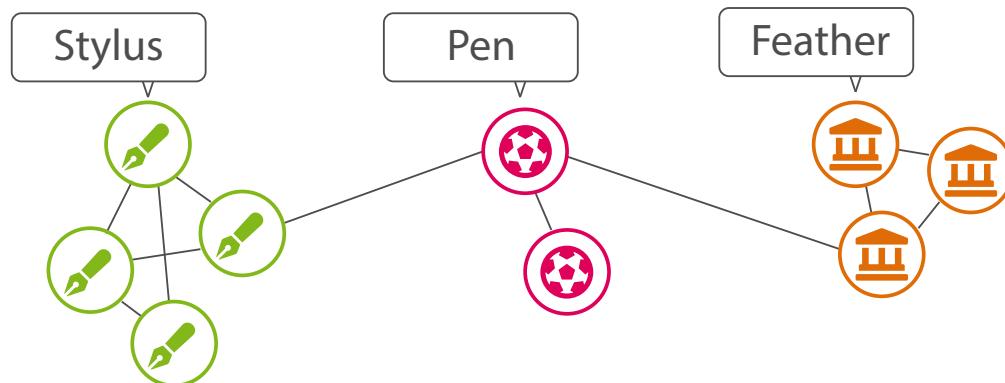
## Motivation

### Celebrity Profiling 2020:

Given the Twitter feeds of the followers of a celebrity, determine the demographics.

How can we profile users that do not write a lot?

- ❑ Author Metadata: Biography, profile picture, ...
- ❑ Author Behavior: Retweets, Likes, ...
- ❑ Social Graph: Homophily and language variation.



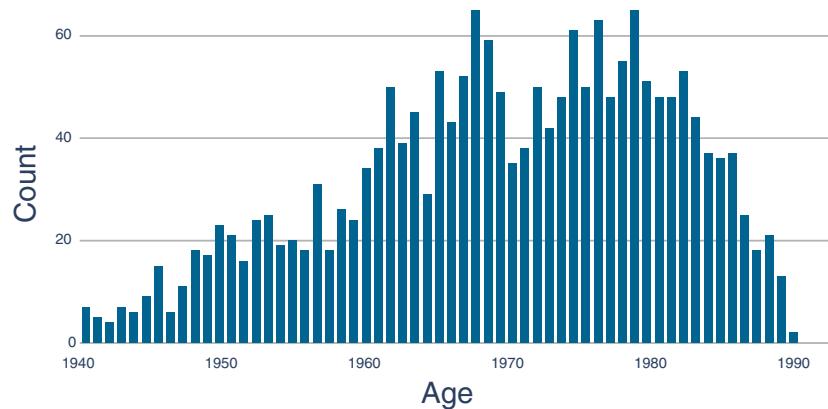
# Celebrity Profiling

## Task

### Celebrity Profiling 2020:

Given the Twitter feeds of the followers of a celebrity, determine the demographics:

- Age,



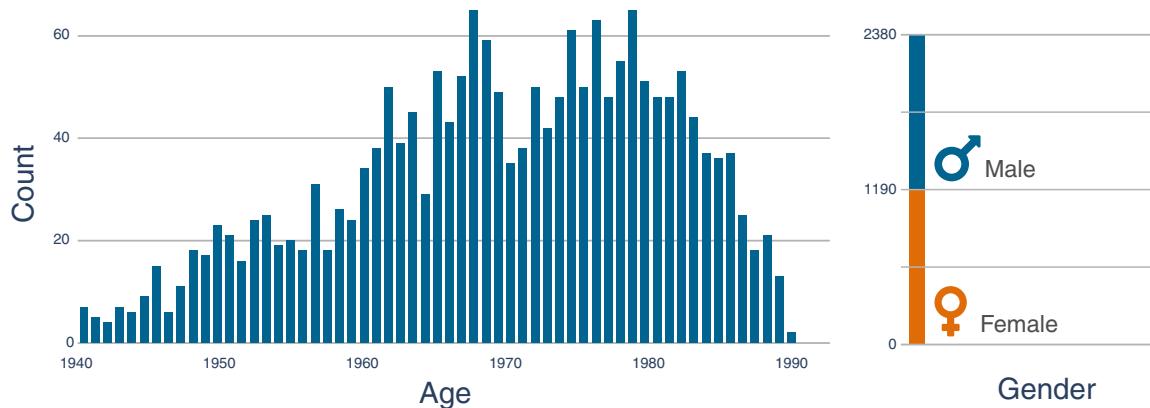
# Celebrity Profiling

## Task

### Celebrity Profiling 2020:

Given the Twitter feeds of the followers of a celebrity, determine the demographics:

- Age,
- Gender,



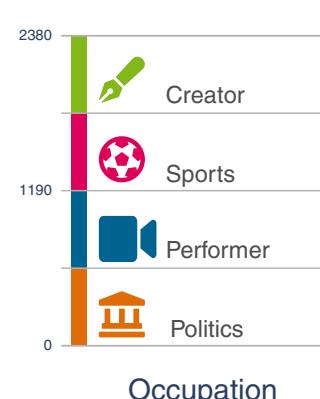
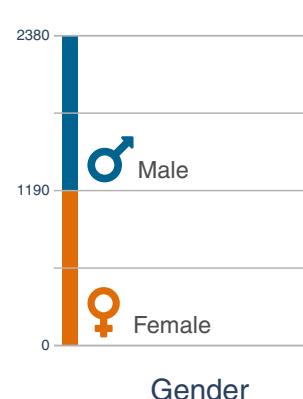
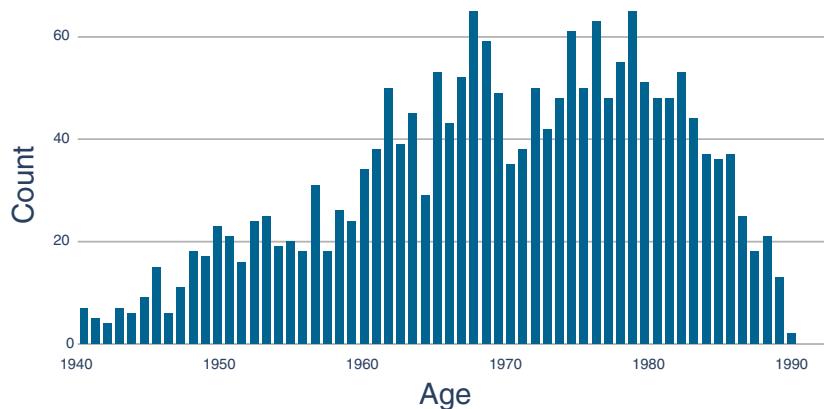
# Celebrity Profiling

## Task

### Celebrity Profiling 2020:

Given the Twitter feeds of the followers of a celebrity, determine the demographics:

- Age**,
- Gender**, and
- Occupation**.



# Celebrity Profiling

## Data

Dataset creation:

1. Extract celebrities with matching profiles from a Corpus [ACL 2019].

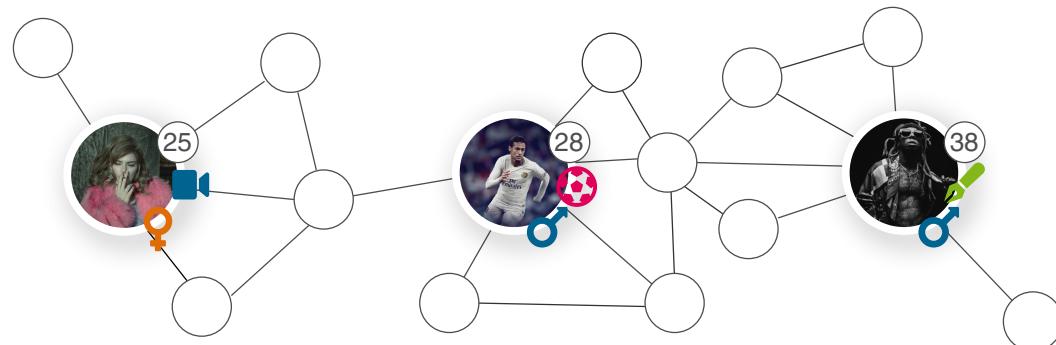


# Celebrity Profiling

## Data

Dataset creation:

1. Extract celebrities with matching profiles from a Corpus [ACL 2019].
2. Download follower network.

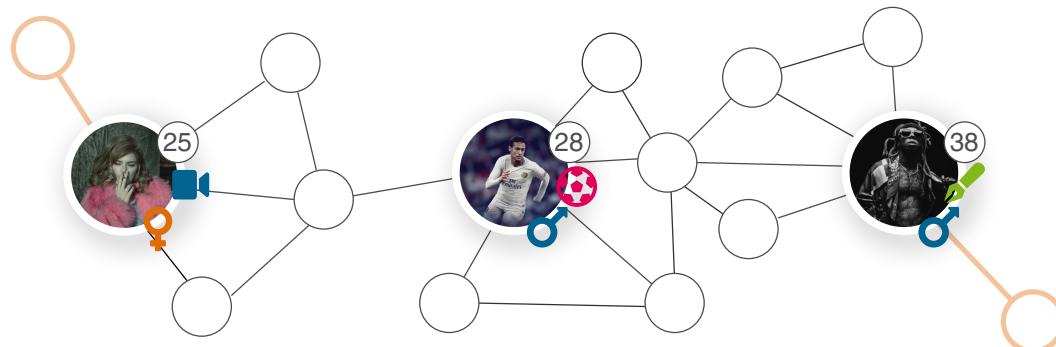


# Celebrity Profiling

## Data

Dataset creation:

1. Extract celebrities with matching profiles from a Corpus [ACL 2019].
2. Download follower network.
3. Eliminate **inactive users**.
  - ❑ Users with few connections in the network.

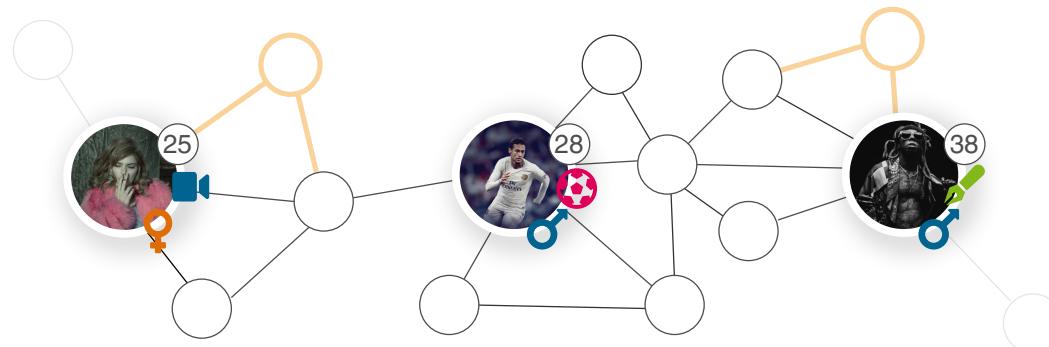


# Celebrity Profiling

## Data

Dataset creation:

1. Extract celebrities with matching profiles from a Corpus [ACL 2019].
2. Download follower network.
3. Eliminate inactive users, **passive users**.
  - Users with less than 100 original, English tweets.

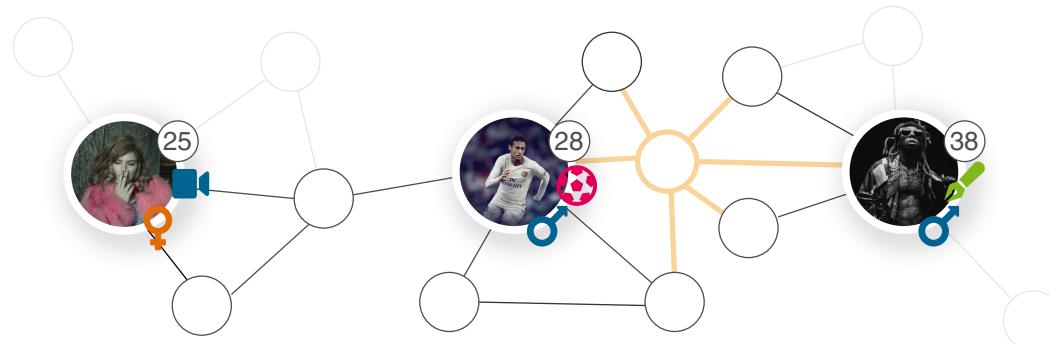


# Celebrity Profiling

## Data

Dataset creation:

1. Extract celebrities with matching profiles from a Corpus [ACL 2019].
2. Download follower network.
3. Eliminate inactive users, passive users, and **other hub users**.
  - Users with many followers or atypical behavior.

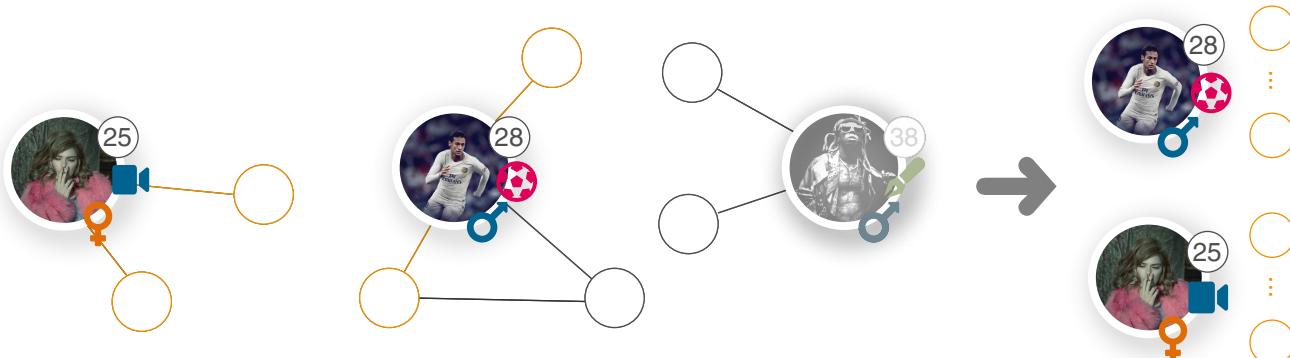


# Celebrity Profiling

## Data

Dataset creation:

1. Extract celebrities with matching profiles from a Corpus [ACL 2019].
2. Download follower network.
3. Eliminate inactive users, passive users, and other hub users.
4. Sample 10 followers per celebrity in a balanced dataset.
  - ❑ **Training dataset:** 1,980 celebrities.
  - ❑ **Test dataset:** 400 celebrities.



# Celebrity Profiling

## Evaluation

Performance is measured as the harmonic mean of the classwise averaged  $F_1$ .

$$cRank = \frac{3}{\frac{1}{F_{1,gender}} + \frac{1}{F_{1,occupation}} + \frac{1}{F_{1,age}}}$$

# Celebrity Profiling

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Variable-bucketed age evaluation:

- Predict author age directly.
- Count near-misses as correct, depending on the age of the author.
- Apply multi-class evaluation.

# Celebrity Profiling

## Results

Baseline:

- ❑ Algorithm: Logistic regression.
- ❑ Features: Bags of word 1 and 2-grams, TD-IDF weighted.
- ❑ Age was predicted in 5 classes: 1947, 1963, 1975, 1985, and 1994.

# Celebrity Profiling

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Trained and tested on **all followers' tweets** as a lower bound.

Participant	Test dataset			
	cRank	Age	Gender	Occupation
baseline-follower	0.47			

# Celebrity Profiling

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- ❑ Age was predicted in 5 classes: 1947, 1963, 1975, 1985, and 1994.

Trained and tested on all followers' tweets as a lower bound.

Trained and tested on **the celebrities' tweets** as a goalpost.

Participant	Test dataset			
	cRank	Age	Gender	Occupation
baseline-oracle	0.63			
baseline-follower	0.47			

# Celebrity Profiling

## Results

As proof of concept: Profiling users from their followers' texts works.

- Baseline was beaten by a healthy margin.

Participant	Test dataset			
	cRank	Age	Gender	Occupation
baseline-oracle	0.63			
Hodge and Price	0.58			
Koloski et al.	0.52			
Alroobaee et al.	0.47			
baseline-follower	0.47			

# Celebrity Profiling

## Results

As proof of concept: Profiling users from their followers' texts works.

- ❑ Baseline was beaten by a healthy margin.
- ❑ Submissions predict young users (20-30) better by .2  $F_1$ .

Participant	Test dataset			
	cRank	Age	Gender	Occupation
baseline-oracle	0.63	0.50		
Hodge and Price	0.58	0.43		
Koloski et al.	0.52	0.41		
Alroobaee et al.	0.47	0.32		
baseline-follower	0.47	0.36		

# Celebrity Profiling

## Results

As proof of concept: Profiling users from their followers' texts works.

- ❑ Baseline was beaten by a healthy margin.
- ❑ Submissions predict young users (20-30) better by .2  $F_1$ .
- ❑ Submissions skew towards the “Male” class.

Participant	Test dataset			
	cRank	Age	Gender	Occupation
baseline-oracle	0.63	0.50	0.75	
Hodge and Price	0.58	0.43	0.68	
Koloski et al.	0.52	0.41	0.62	
Alroobaee et al.	0.47	0.32	0.70	
baseline-follower	0.47	0.36	0.58	

# Celebrity Profiling

## Results

As proof of concept: Profiling users from their followers' texts works.

- ❑ Baseline was beaten by a healthy margin.
- ❑ Submissions predict young users (20-30) better by .2  $F_1$ .
- ❑ Submissions skew towards the “Male” class.
- ❑ Submissions beat the oracle on occupation, although “Creators” is a problematic class (.46  $F_1$ ).

Participant	Test dataset			
	cRank	Age	Gender	Occupation
baseline-oracle	0.63	0.50	0.75	0.70
Hodge and Price	0.58	0.43	0.68	0.71
Koloski et al.	0.52	0.41	0.62	0.60
Alroobaee et al.	0.47	0.32	0.70	0.60
baseline-follower	0.47	0.36	0.58	0.52

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## Outlook

We still have many open questions:

- Does the communities' text reflect the demographics of a celebrity?

# Celebrity Profiling

## Outlook

We still have many open questions:

- Does the communities' text reflect the demographics of a celebrity?
- Do celebrities influence the writing of their fans?
- What are the rules of style formation?

See you at CLEF 2021!