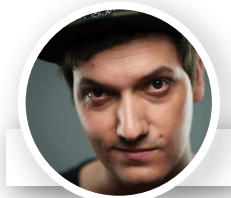


# Overview of the Celebrity Profiling Task at PAN 2020

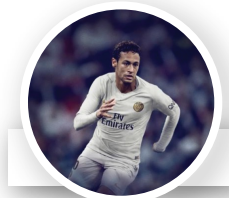
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**LeFloid** 🇺🇸  
@LeFloid



**Kendall** ✓  
@KendallJenner



**Neymar Jr** ✓  
@nejmarjr



**Lil Wayne WEEZY F** ✓  
@LilTunechi

**Matti Wiegmann**, Benno Stein, Martin Potthast  
Bauhaus-Universität Weimar  
webis.de

# 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, ...



# 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

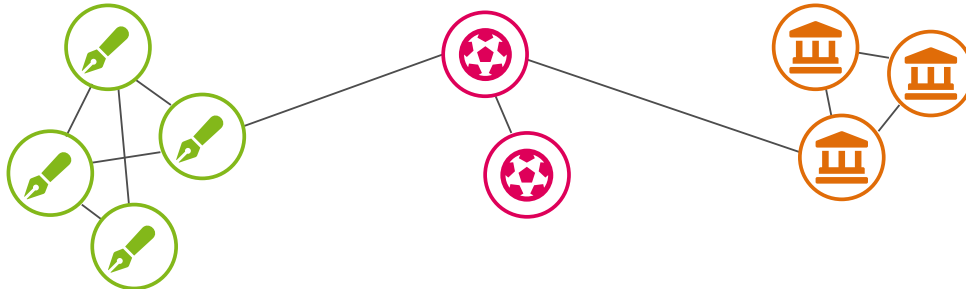
## Motivation

### 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

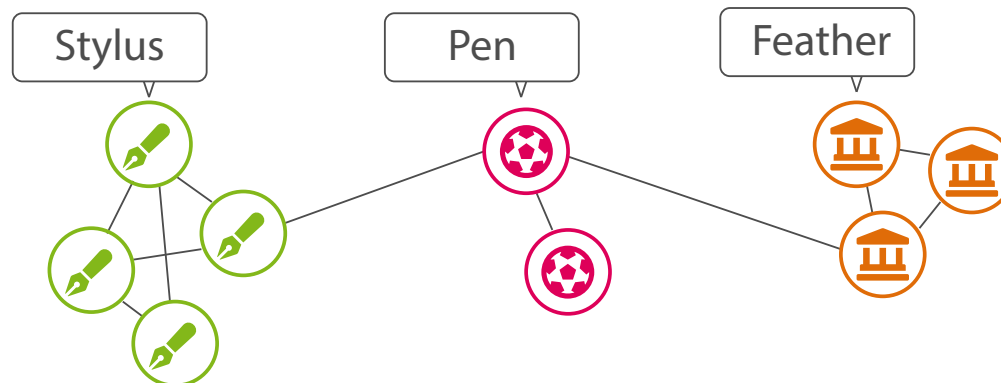
## Motivation

### 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**.



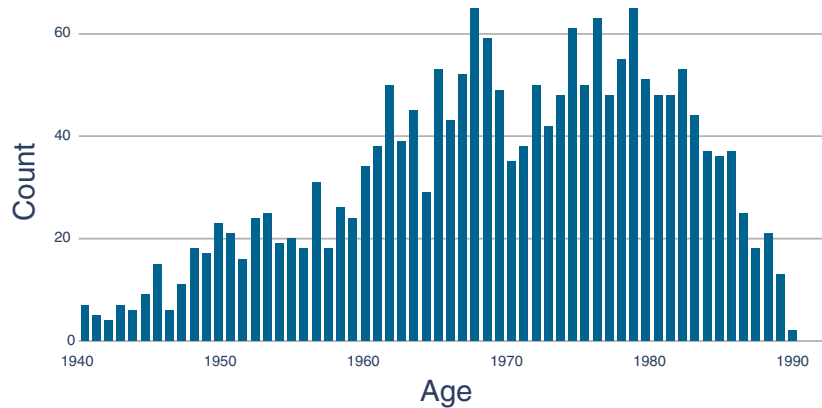
# Celebrity Profiling

## Task

### Celebrity Profiling 2020:

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

- **Age,**



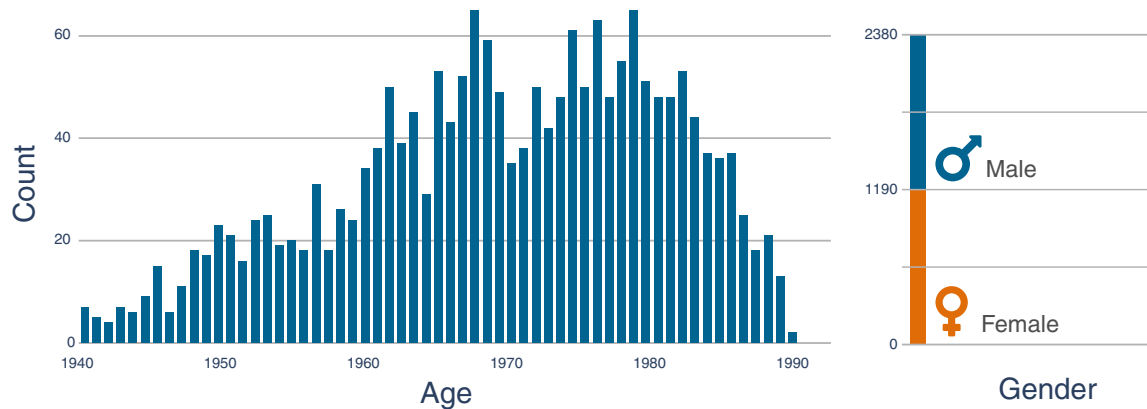
# Celebrity Profiling

## Task

### Celebrity Profiling 2020:

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

- ❑ **Age,**
- ❑ **Gender,**



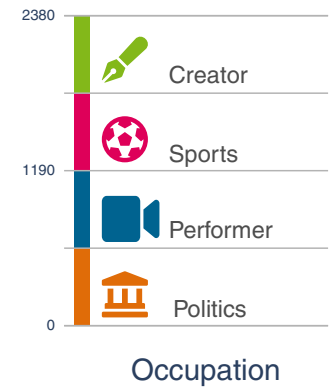
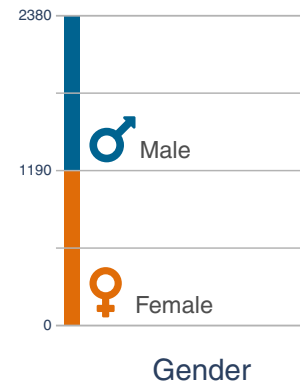
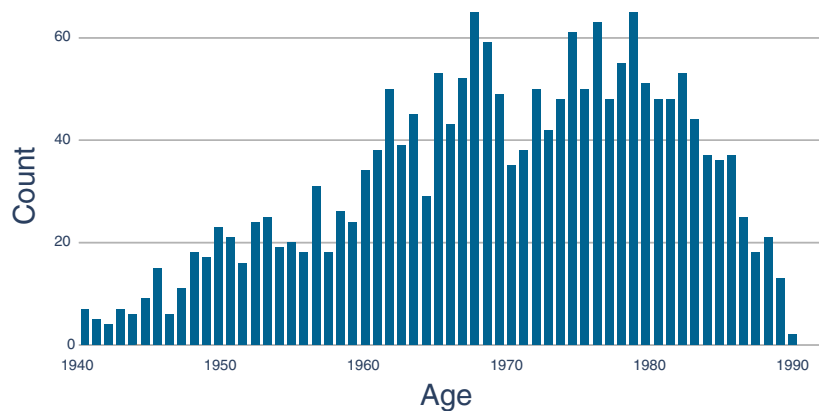
# Celebrity Profiling

## 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].

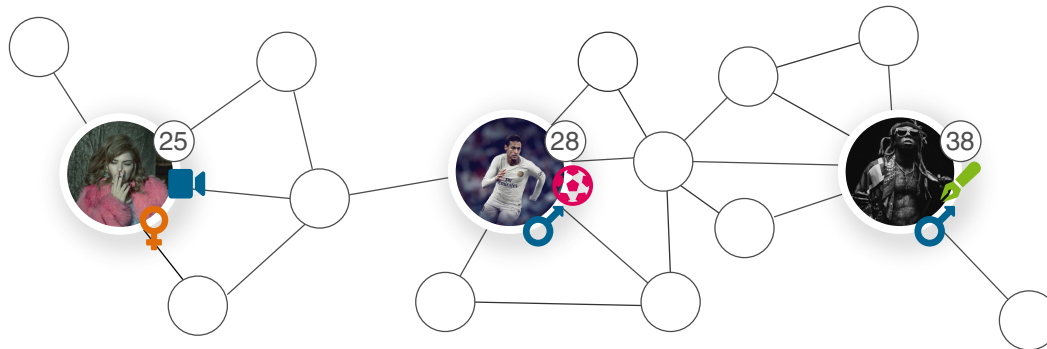


# Celebrity Profiling

## Data

Dataset creation:

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

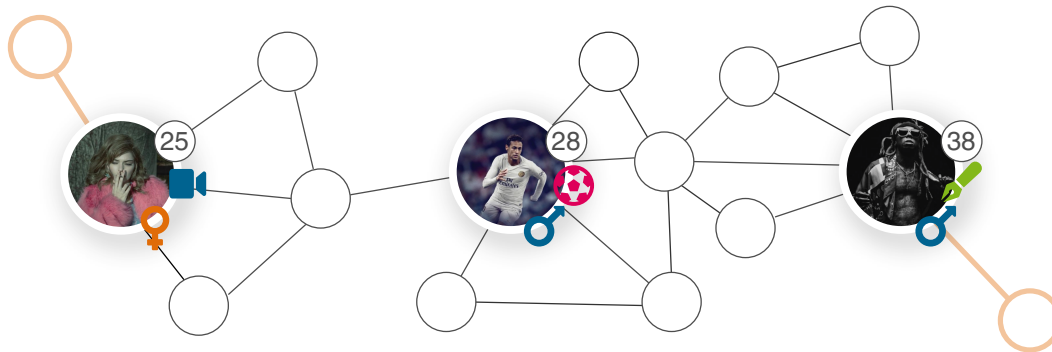


# Celebrity Profiling

## 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.

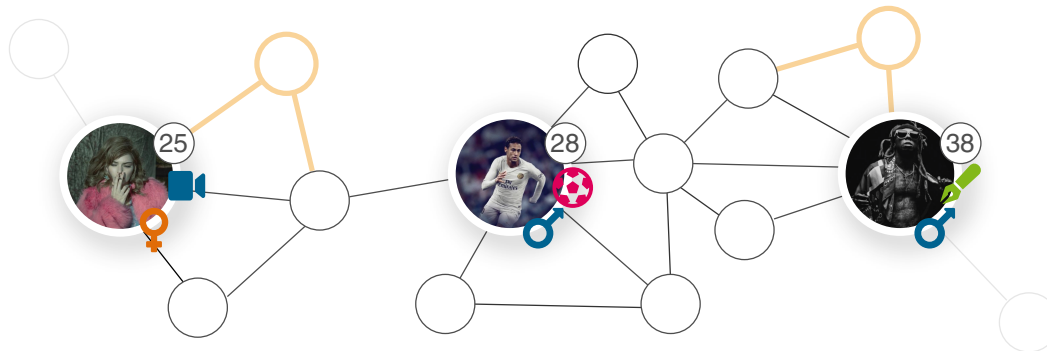


# Celebrity Profiling

## 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.

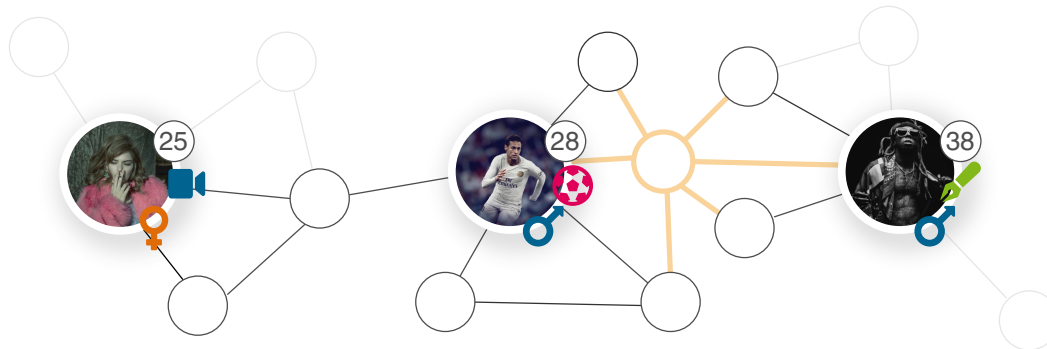


# Celebrity Profiling

## 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.

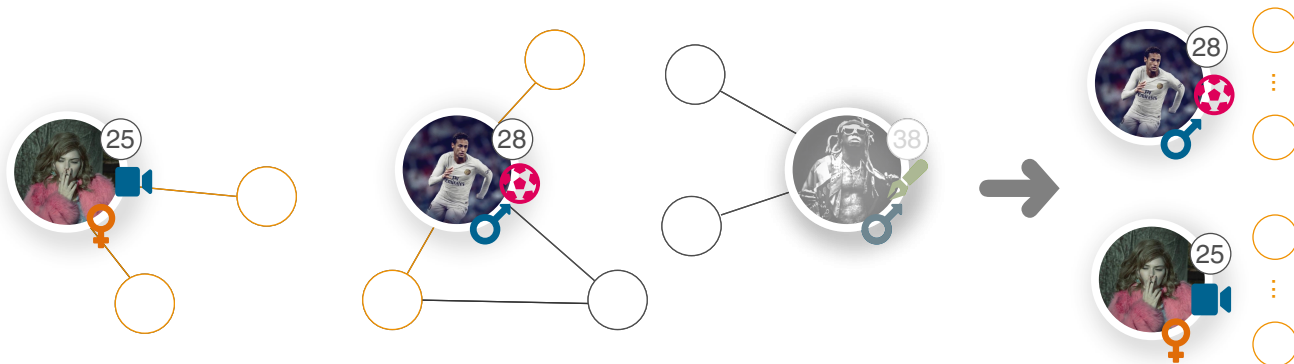


# Celebrity Profiling

## 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  $F_1$ .

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

# Celebrity Profiling

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

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.

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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

## Results

Baseline:

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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			
Alroobaea 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		
Alroobaea 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	
Alroobaea 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
Alroobaea et al.	0.47	0.32	0.70	0.60
baseline-follower	0.47	0.36	0.58	0.52

# Celebrity Profiling

## 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!