SICSS Edinburgh

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## CSS in Practice

# Predicting User’s Attributes

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# Task/Purpose

- Learn/Predict something about a given user
- Learn/Understand characteristics of certain user groups
- Consideration: ETHICS
- Examples RQs:
    - Can we predict users' actions in the future?
    - Can we predict users' hidden information?
    - What makes a given user have a given leaning?
- Example applications: predicting voting, extremism …

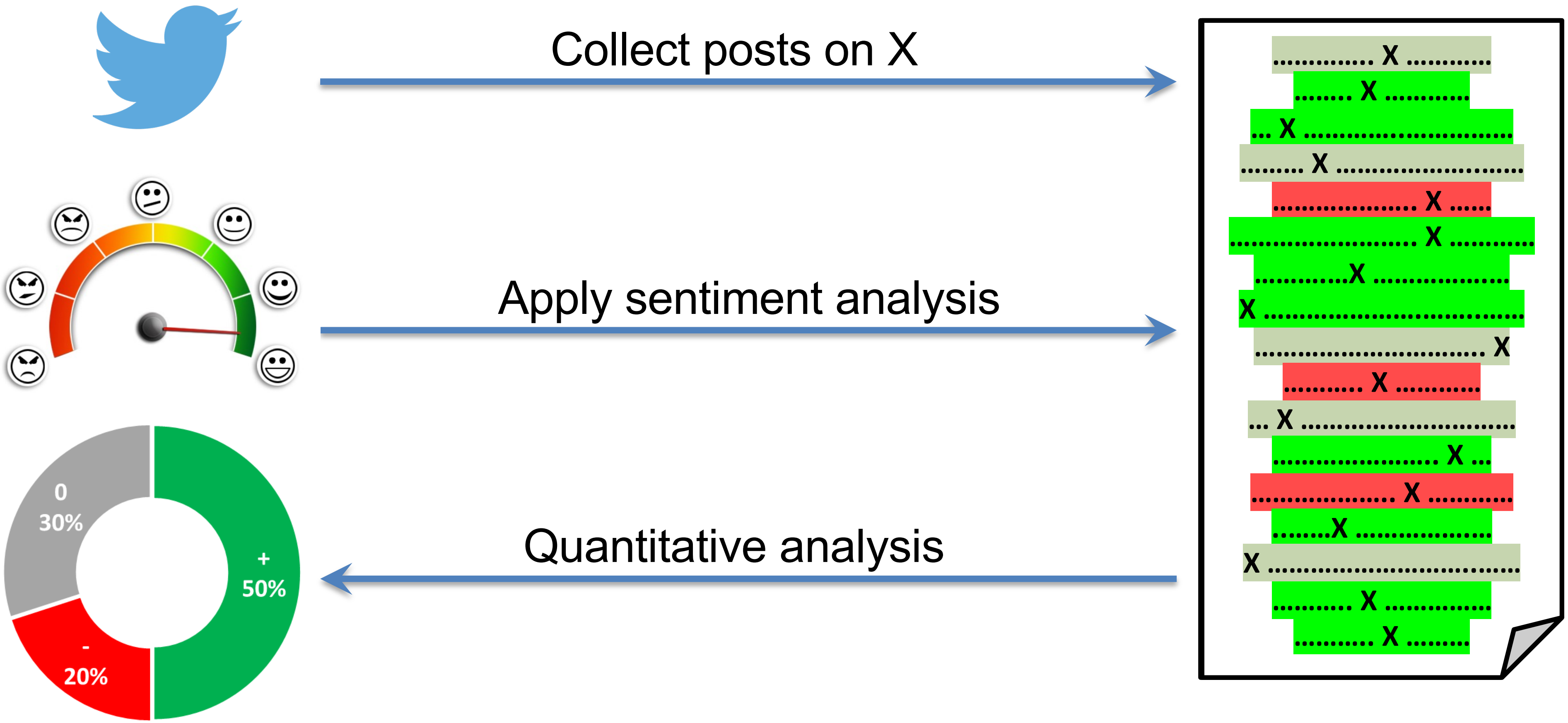
# Outlines

- Examples of using CSS for predicting user's information

- 6 Example Studies
- No technical details (ask if you need details)
- Sharing main methodology
- Topics: might be sensitive!!

# Important Note: Using Sentiment to Measure Support

# How People Think about Topic X?



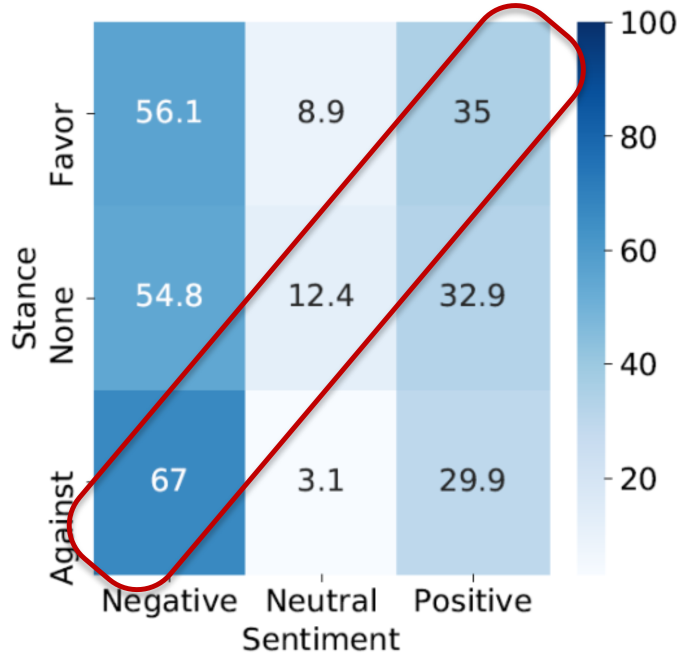
# Common Practice

- How people think about **X** (e.g. ~~*iPhone14*~~ ***Trump***, ~~*SICSS*~~ ***Brexit***)?
- Collect posts mentioning **X**
- Use sentiment analyser to check posts polarity
- Result: 50% positive, 20% negative, 30% neutral
- Conclusion: 50% of posts ~~likes~~ supports **X**, while 20% are ~~negative to~~ against it.

- Can we use **sentiment** to measure **support** (stance)?

# Sentiment vs Stance

- Sentiment = emotion polarity in text
- Stance = position towards a given tc
- SemEval topics labelled independer Sentiment & Stance




- Measure agreement
- **No**, you cannot use sentiment to measure support!
- e.g.: "I am sad that Hillary lost ☹"
  "*Trump is visiting Florida #MAGA*"

# Lesson

- **Sentiment ≠ Stance**
- **When measuring support on a given topic/entity, use a stance classifier not a sentiment analyser**

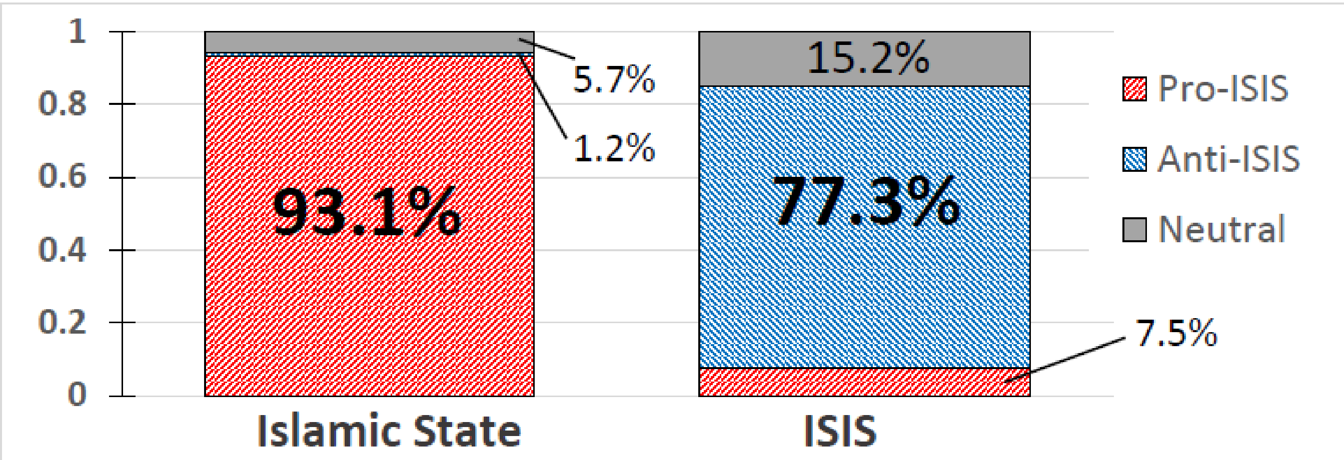
## Ref:


- Aldayel A. and W. Magdy. Assessing Sentiment of the Expressed Stance on Social Media. SocInfo 2019

# Antecedent of Support?

# Where ISIS supporters come from?

- Signals of ISIS support is frequently noticed on SM
- Collected 3 million tweets mentioning ISIS
- Labeling:




- 57K (11K + 46K) users talking about ISIS (10 tweets at least)

# Data Collection

- Collect tweets timeline for **57K** users → **123 million** tweets
- Identify tweets of users before even mention ISIS
- Filter-out accounts with no pre-ISIS data

# Classifier

- Pro-ISIS accounts with pre-ISIS tweets = **7,700** users
- Balance Data: random select **7,700** Anti-ISIS account with pre-ISIS tweets
- Train classifier with Pre-ISIS tweets
- Mission: Predict if the user will be in the future **Pro-** or **Anti-** ISIS
- Features: tweets content (BOW)

- Accuracy → **87%**
- **Analysis:**
  - Find most distinguishing feats for Pro-ISIS *(before being supporters to ISIS)*

# Findings

- **Most distinguishing features:**
  - Related to Arab spring (Egypt, Syria, Libya)
  - Related to protesting against Arab regimes (SA, Kuwait, Iraq)
- **Qualitative**

| Date | Tweet (translated) |
|---|---|
| May 25, 2012 | Don't be surprised if it rains today ... martyrs are spitting on us |
| Nov. 9, 2014 | Preliminary schizophrenia: I like ISIS, but I want to watch Chris Nolan's new movie |
| Nov. 17, 2014 | Check the gazes of Bashar's soldiers before slaughter by #Islamic_State in #despite_the_disbelivers |

- **Support of ISIS is <u>not ideological</u>, but for <u>revenge</u>**

# Methodology

- Use old textual data on user's social media page to predict their potential future leanings

## Ref:


- Magdy W., K. Darwish, and I. Weber. "I like ISIS, but I want to watch Chris Nolan's new movie": Exploring ISIS Supporters on Twitter. *Hypertext 2015*
- Magdy W., K. Darwish, and I. Weber. #FailedRevolutions: Using Twitter to Study the Antecedents of ISIS Support. *First Monday, 2016*

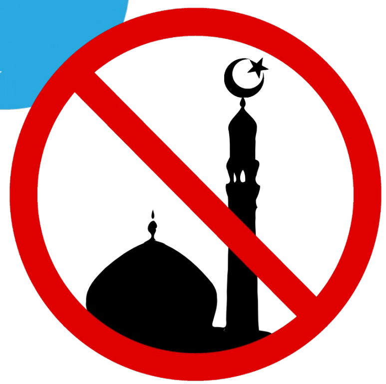
# Predicting Unseen Views!

# #ParisAttacks

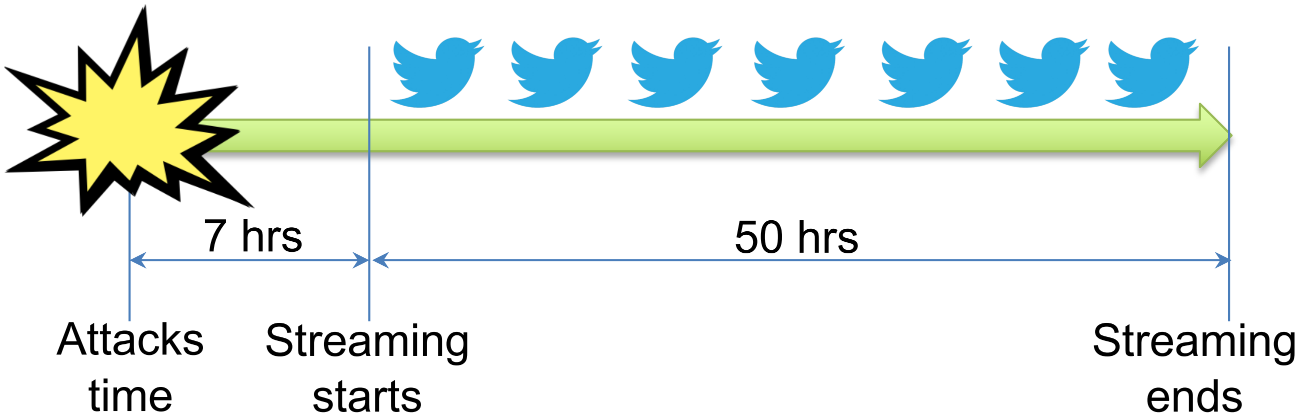

November 13, 2015

# #ParisAttacks – next few hours

#Pray4Paris

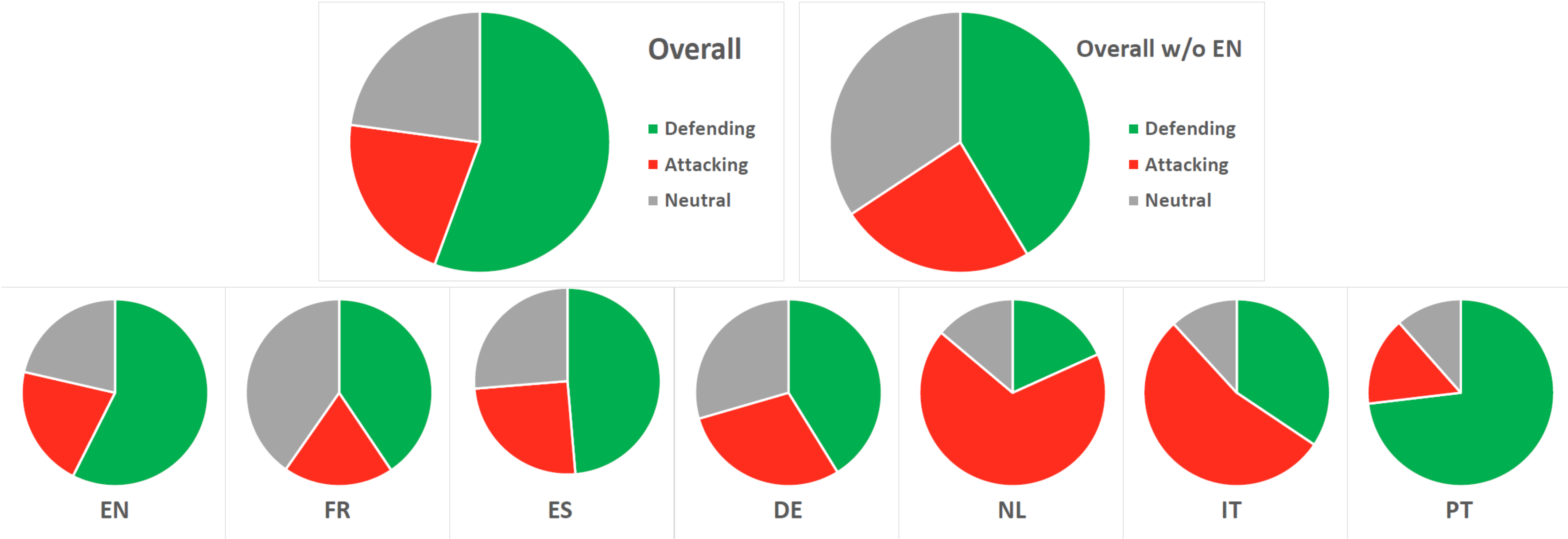


# #ParisAttacks – Data Collection



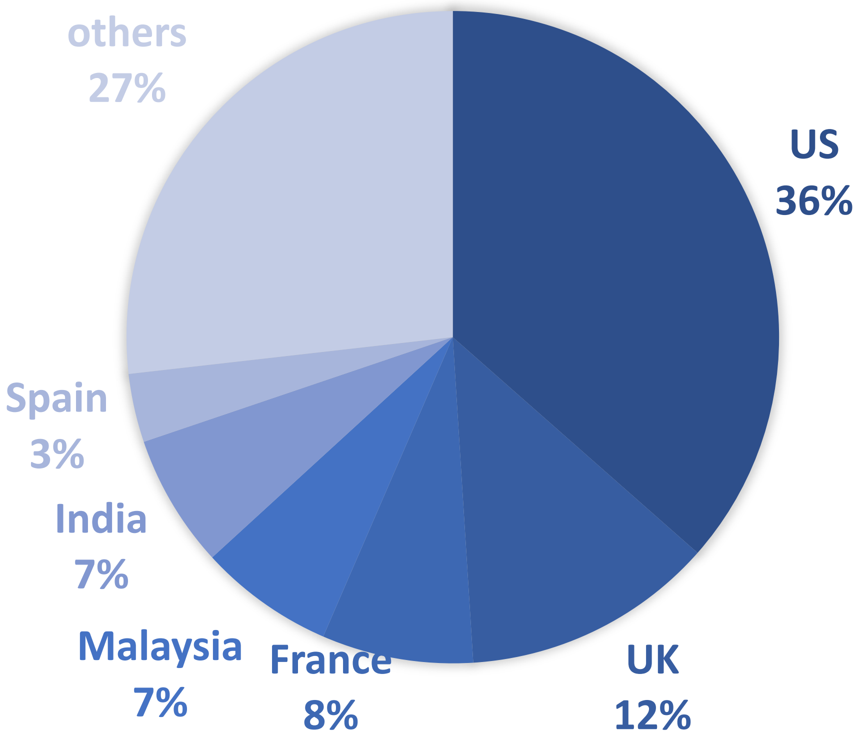

- Collection: **8.4 million** tweets about #ParisAttacks
- **900K** tweets talking about Islam
- Sampling + label propagation → **336K** tweets *(in 10 languages)*
  Attacking Muslims / Defending Muslims / Neutral

# #ParisAttacks – Stance → Muslims




Stances towards Muslims after Paris Attacks by language

# #ParisAttacks – Top Countries




Top countries tweeted about Muslims after Paris Attacks

| Top Defending Countries | Top Attacking Countries |
|---|---|
| KSA | Israel |
| Jordan | Netherlands |
| Indonesia | France |
| Maldives | India |
| Pakistan | Georgia |
| Qatar | Italy |
| Kuwait | Colombia |
| Nigeria | Switzerland |
| Ghana | US |

# #ParisAttacks – Top Hashtags

| Positive | Count | Negative | Count |
|---|---|---|---|
| #MuslimsAreNotTerrorist | 34,925 | #IslamIsTheProblem | 3,154 |
| #MuslimAreNotTerrorist | 17,759 | #RadicalIslam | 1,618 |
| #NotInMyName | 4,728 | #StopIslam | 1,598 |
| #MuslimsStandWithParis | 1,228 | #BanIslam | 460 |
| #MuslimsAreNotTerrorists | 1,106 | #StopIslamicImmigration | 333 |
| #ThisisNotIslam | 781 | #IslamIsEvil | 290 |
| #NothingToDoWithIslam | 619 | #IslamAttacksParis | 280 |
| #ISISareNotMuslim | 316 | #ImpeachTheMuslim | 215 |
| #ExtremistsAreNotMuslim | 306 | #KillAllMuslims | 206 |
| #ISISisNotIslam | 243 | #DeportAllMuslims | 186 |

# Research Questions

- Can we predict user stances?
- What if the user never talked about the topic before?
- What are the key features?

- US-based polarized users → 44K users
- Latest 400 tweets/user before attacks + Profile info
- 12.6M tweets + Network interactions + Profile info

# Predicting Stances

- **Features:**
  - **Content:** BOW, hashtags
  - **Profile:** name, desc., location
  - **Network:** retweets, replies, mentions
- **SVM + linear kernel**
- **10-fold cross-validation**
- **Divide to:**
  - **Mentioned Islam before** (10.5K → 6.6K+4K)
  - **Never mentioned Islam** (33.5K → 27.5K+6K)

# Results

| Features Set | Mentioned-before | | Never mentioned-before | |
|---|---|---|---|---|
| | *Accuracy* | *F-score* | *Accuracy* | *F-score* |
| Content | 0.83 | 0.82 | 0.84 | 0.73 |
| Profile | 0.73 | 0.70 | 0.79 | 0.62 |
| Network | **0.86** | **0.85** | **0.88** | **0.77** |
| All | 0.85 | 0.84 | 0.87 | 0.76 |

- **Network interactions are the most effective features**
- **Predictability is high even for users never mentioned the topic before**

# Feature Analysis

## Defending Muslims

THE HUFFINGTON POST

THE NEW YORKER

BLACK LIVES MATTER

LOVE WINS

NRA

EDM ELECTRONIC DANCE MUSIC

Acabella

## Attacking Muslims

FOX NEWS

NFL

NHL

theblaze

NASCAR

DRUDGE REPORT

#TCOT

# Lessons

- People's unspoken views are predictable
- User's network is a key factor for future behavior
- Humans tend to group into homophily, even on SM
- 

## Ref:

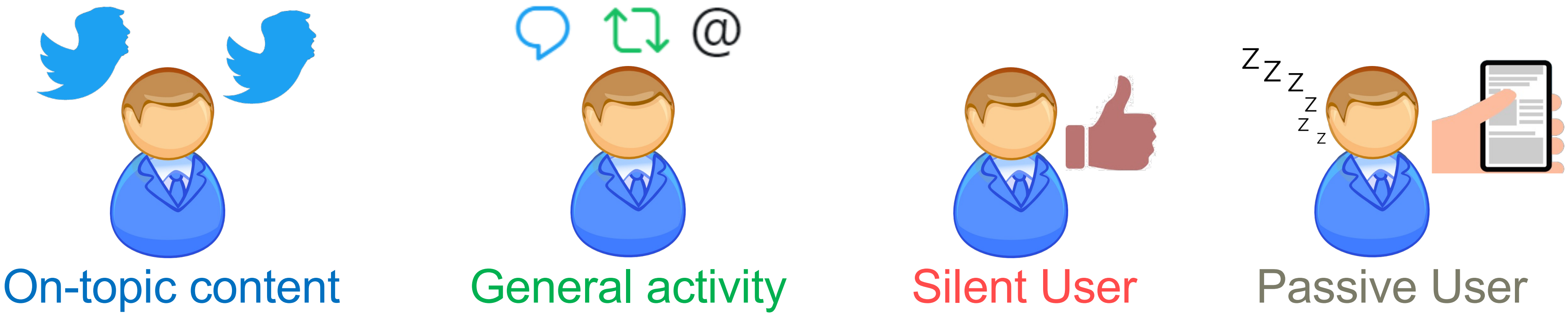

- Magdy W., K. Darwish, A. Rahimi, N. Abukhodair, T. Balswin. #ISISisNotIslam or #DeportAllMuslims? Predicting Unspoken Views. *Web Science 2016*
- Darwish K., W. Magdy, A. Rahimi, N. Abukhodair, T. Baldwin. Predicting Online Islamophopic Behavior after #ParisAttacks. *Journal of Web Science 2017*

# What can reveal your Stance?

# SemEval Stance Detection Task 2016

- **4K** tweets on **5 topics** labeled by stance {for, against, none}
- Topics: *Abortion, Atheism, Feminism, Clinton, & Climate Change*
- State-of-the-art:
  - SVM + n-gram features → F-score **69%**
  - Other approaches: deep learning → F-score < 69%
  - Focus on content features only! → user discussed the topic!
- RQ: How detecting stance could be done if:
  - User never discussed the topic!
  - User never tweeted, but has some online activity!
  - User has no content and no activity!

# Detecting Stance in Four Situations




- TXT: tweet Text content
- IN: Interaction Network → network user retweet, reply, mention
- PN: Preference Network → network in tweets user like
- CN: Connection Network → network user follows

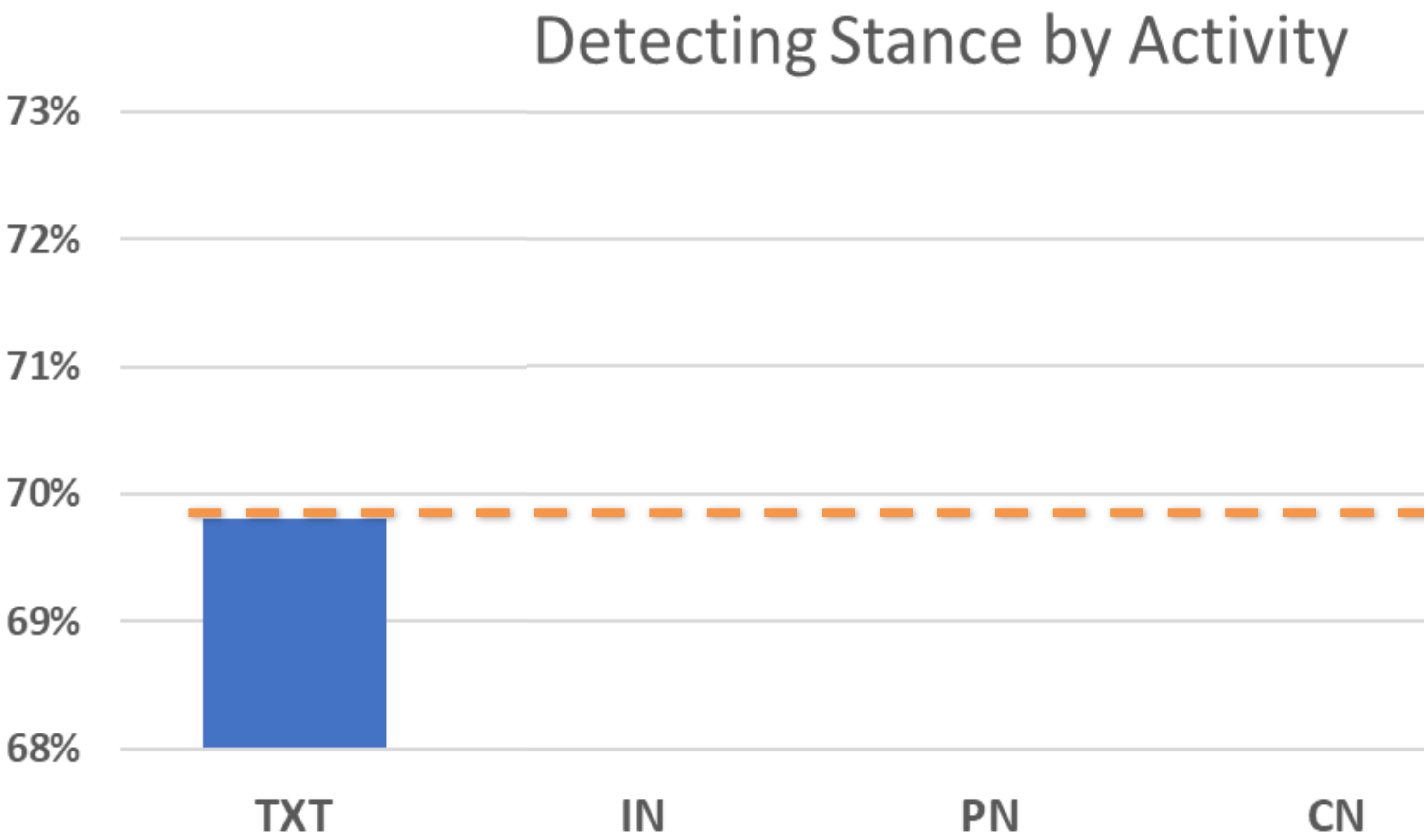
# Experimental Setup

- Four types of features
  - Text
  - Interaction network (whom you retweet, mention, reply)
  - Preference network (whom you like their content)
  - Connection network (whom you follow)

- Classifiers: SVM, LR, RNNs … etc
  - SVM achieved the best!

- Analyze commonality between networks

# What can reveal your stance?




*what you say* | *your activity* | *your preferences* | *your existence* | *combine them*

# Lesson

- **Every activity for us online can give indication about our stances and leanings, whether we express it or not!**

## Ref:


- Aldayel A and W. Magdy. Your Stance is Exposed! Analysing Possible Factors for Stance Detection on Social Media. *CSCW 2019*

# Fake Accounts / Catfishes
# Can your style online show you are fake?

# Catfishes

- Catfish: pretends different person

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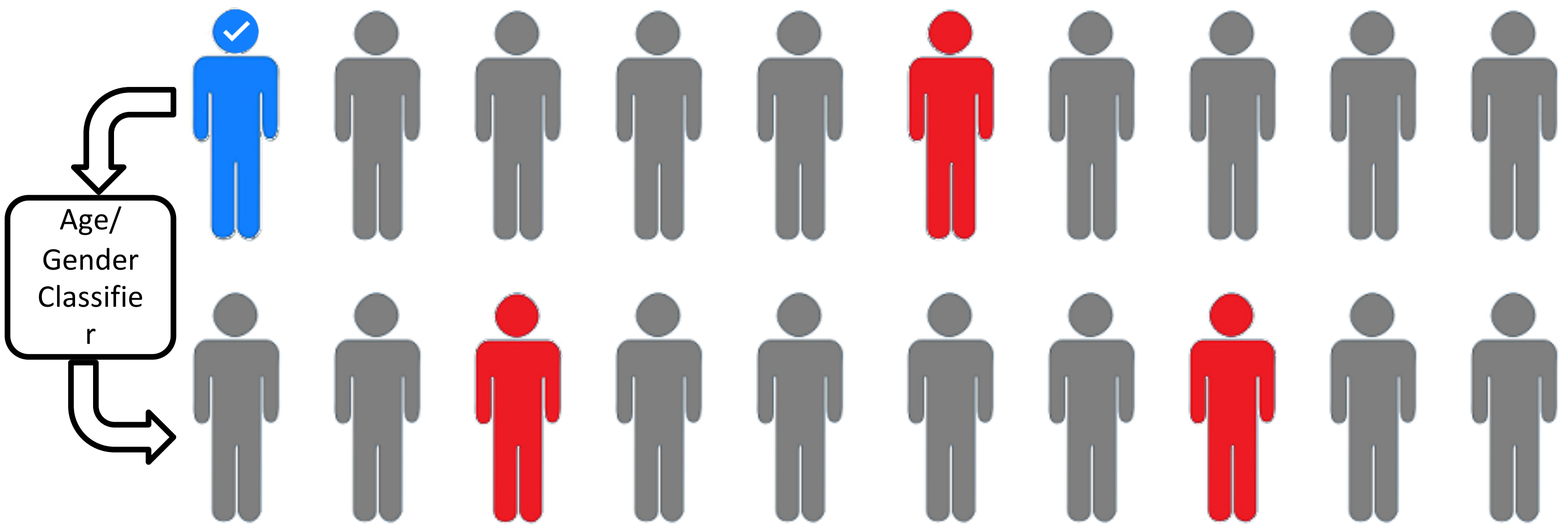
# Data/Approach

- 100K user accounts
- 5% verified accounts

Pornhub



# Predicting Gender & Age

Gender

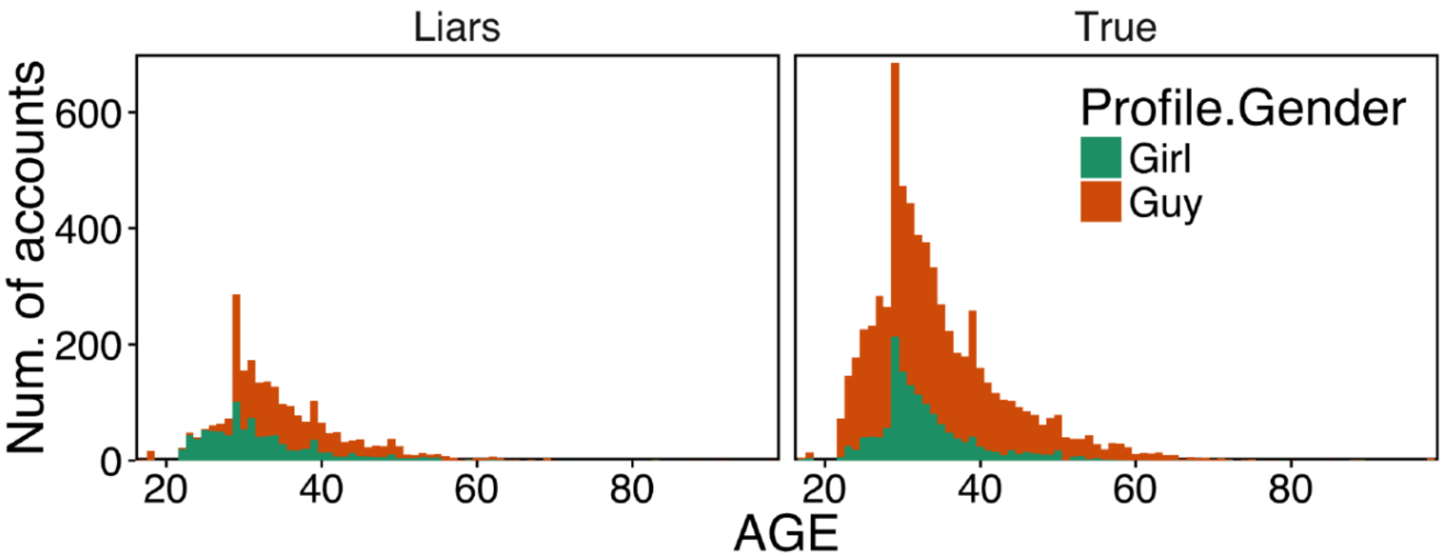
| Features | Accuracy |
|---|---|
| Comments | 85.9% |
| Network/Activity | 88.7% |
| **All** | **92.0%** |

Age

| Features | Correlation | MAE (yrs) |
|---|---|---|
| **Comments** | **0.509** | **5.58** |
| Network/Activity | 0.234 | 6.12 |
| All | 0.440 | 5.78 |

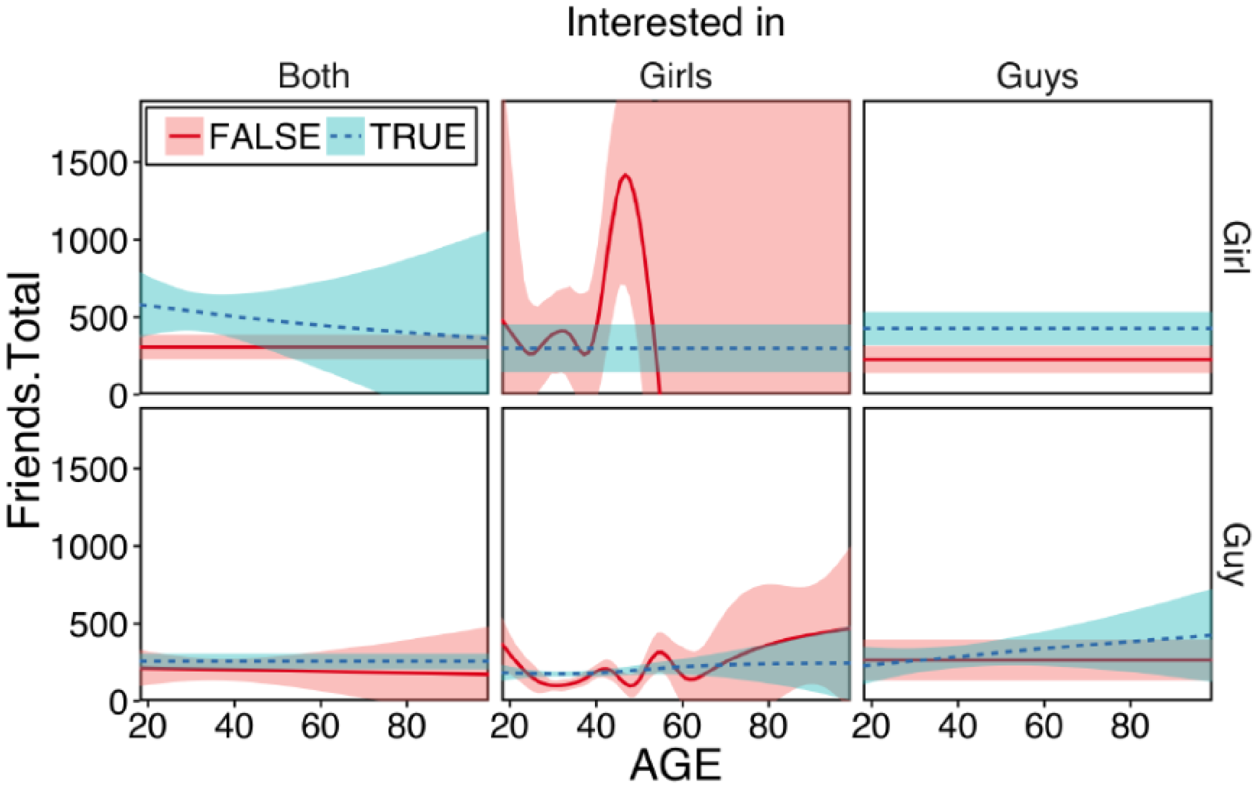
# Who Catfishes?

- **25%** are likely lying about their age
- Males pretend to be young females
- Females pretend to be older males



# Why Catfishing?

- Girls want peace / Guys want popularity



# Lesson

- **From your online public social activity, hidden personal information could be estimated**

## Ref:


- Magdy W., Y. Elkhatib, G. Tyson, S. Joglekar, N. Sastry. Fake it till you Make it. Fishing for Catfishes. *ASONAM 2017*

# Prediction is sometimes Scary!

# Demographic Prediction

- Different research showed that demographic information can be predicted about users using their posts
- Experiment:
  - Collected timelines of **20,000** Twitter users (WW, NYC, London, Johannesburg)
  - Annotate <u>ethnicity</u> and <u>gender</u> of user based on profile pic.
  - Use their posts to predict their demographics

Male
Female

| Classifier | Accuracy |
|---|---|
| Gender | 80.6% |
| Ethnicity | 85.2% |

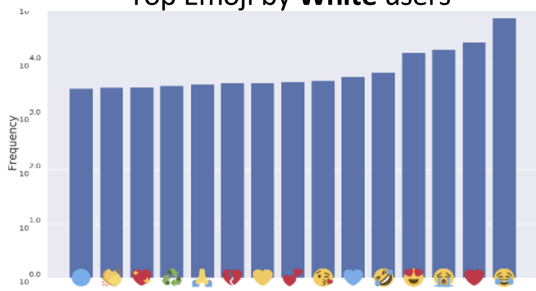
White
Black
Others

# What about the Emoji they use?

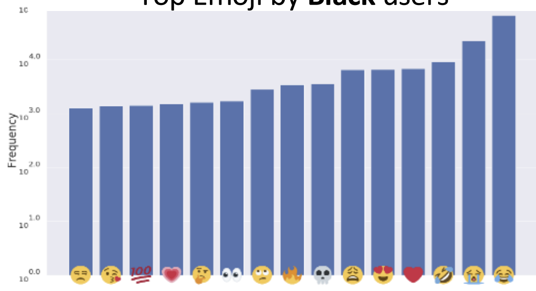
- There are **2600** emoji out there!
- **20%** of social media posts contain emoji
- Does general emoji usage differ by demographic?
- Can we use them for prediction instead of text?

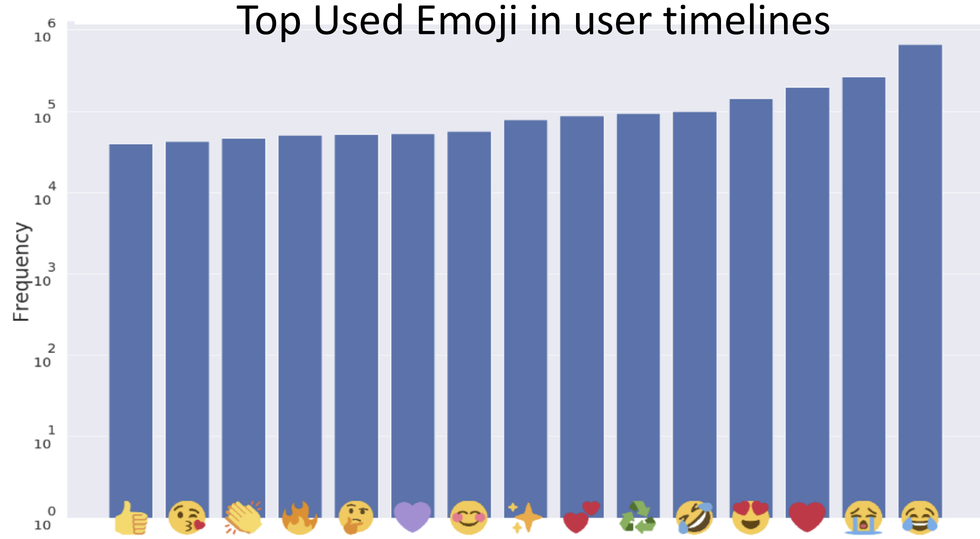
# Top Used Emoji

Top Emoji by **White** users

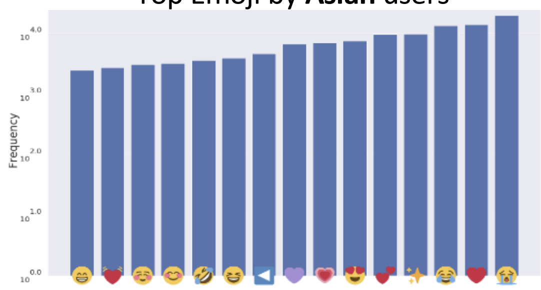



Top Emoji by **Black** users

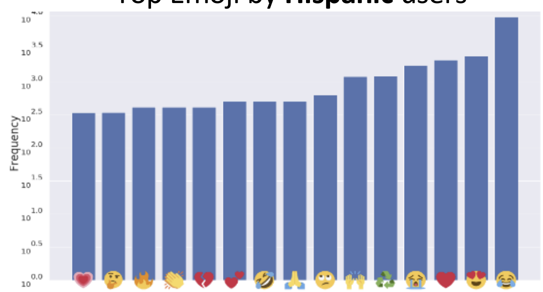


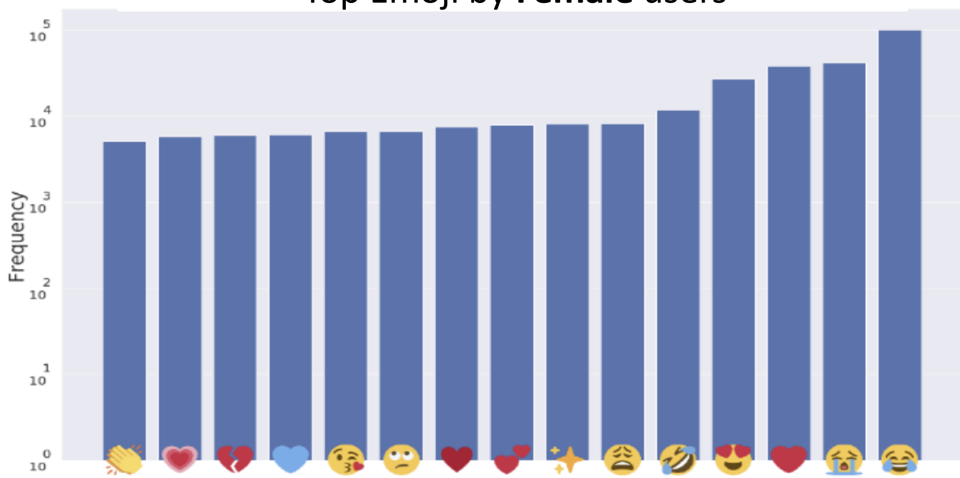

Top Emoji by **Asian** users



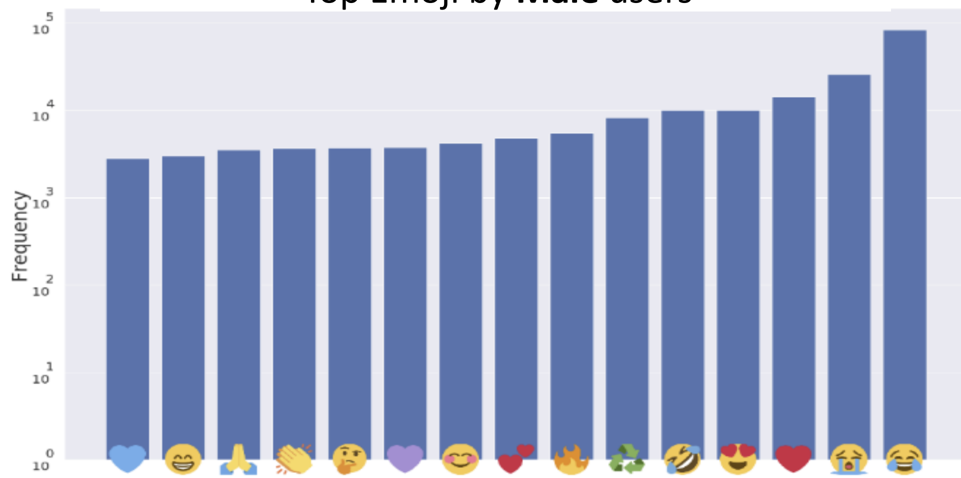

Top Emoji by **Hispanic** users



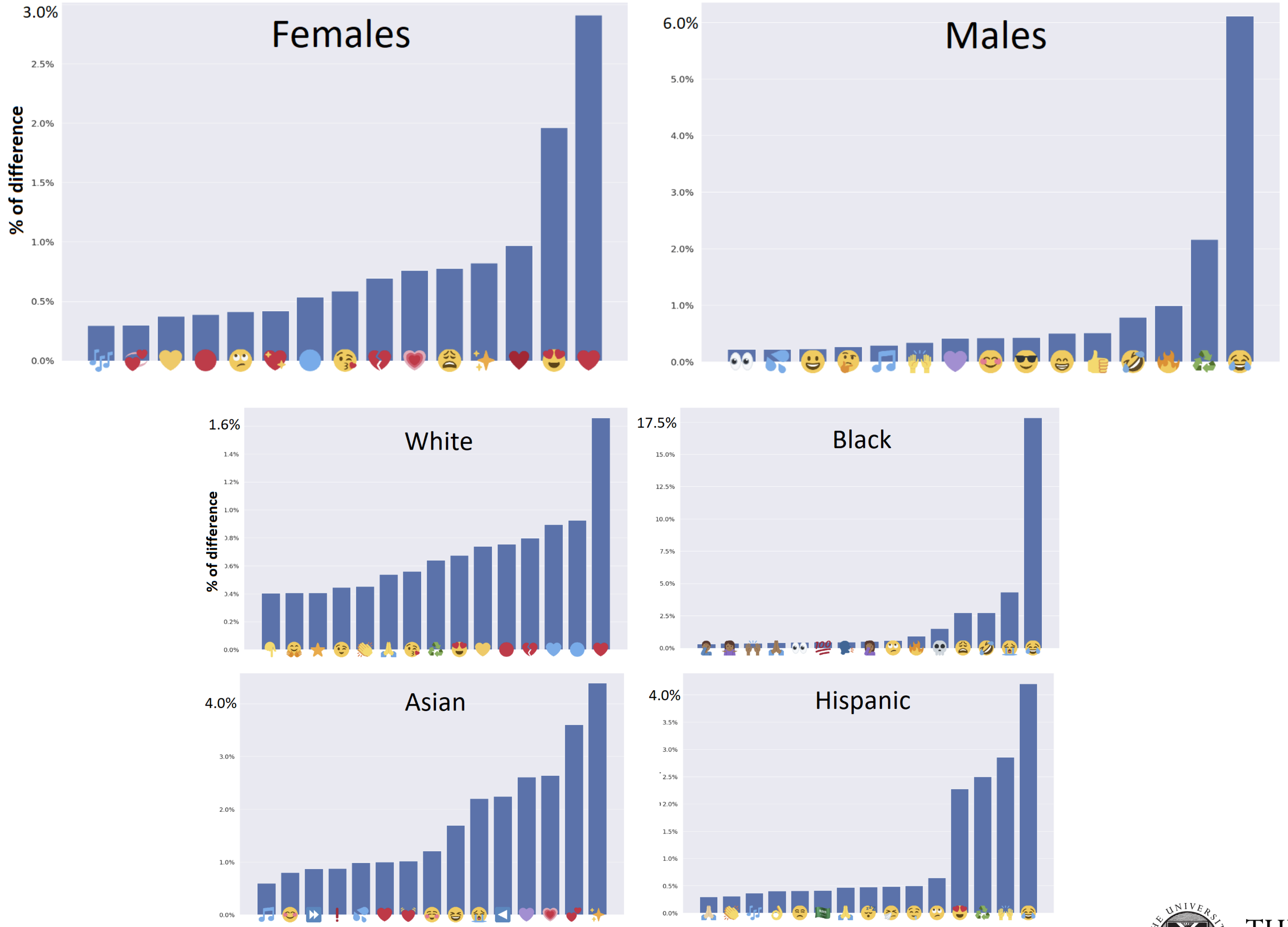

Top Emoji by **Female** users




Top Emoji by **Male** users



# Difference in Usage by Demographics



# Demographics Estimation by Emoji

- Are these differences enough to estimate user's demographic information?
- Train classifiers for gender/race using emoji in timeline only!

| Classifier | Posts | Emoji |
|---|---|---|
| Gender | 80.6% | 80.4% |
| Ethnicity | 85.2% | 84.5% |

# Lesson

- Minor signals in our posts online, such as emoji, can tell a lot about our identity, including gender and ethnicity.

## Ref:


- Emoji Usage Variation by Gender and Race on Twitter*. unpublished*

# Takeaways

- We have many signals and footprints online
- These signals can be used to infer information about us.
- We can predict user’s leanings, biases, and demographics
- CSS is a method to make us learn about ourselves and our societies in a fast way → ETHICS
- Can be an excellent informative motivation for more in depth social studies.

- Presented work was using <u>public</u> social media data,
  → Think about the data that companies own!

# Final Words

- **Computational Social Science**
- **Interdisciplinary field**
  - Social Science + Computer/Data Science
- **Conferences**:
  - CSCW, ICWSM, CHI, the WebConf, WebSci, SocInfo, ASONAM
- **Journals**:
  - Nature Human Behavior, ACM TSC, Springer SNAM
- **NLP**:
  - Models: Huggingface
  - Tasks: SemEval

# SMASH Members

SMASH
Social Media Analysis and Support for Humanity

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