Predicting Emoji Usage for a Recommender System

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Problem Description

Emojitracker
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Emojis, Emojis everywhere

emojitracker: realtime emoji use on twitter

1055243340	580449867	471108721	431521146	345967697	324085449	313781984	271272819
266253888	263924852	251619883	246904155	216046535	202974706	198442656	133402319
130212638	127275356	118696415	118242683	118127577	110785355	109616142	109265799
103435721	99036465	96831203	90809972	90793619	90081405	89821603	88764875
86592181	86046163	85626133	84234882	80873410	78845347	78625365	78426373
77702794	77361511	75642628	73614253	73322516	68324181	67711119	66586209
66000108	65685353	65074643	61218545	59095859	56502263	53149554	53114601
50255918	49645874	49226507	47786178	47497919	47339432	46661267	45711234
45183925	43908499	43165247	41924782	40957757	40304641	40098486	39258281
38869185	38257495	38077005	38003656	37286093	37035146	36911739	33341665
32161683	31894311	31766179	30890414	30607973	30288921	28674491	28661904
28522853	28239791	28016528	27488797	26262417	26144526	26135627	26037534
25560056	24494728	24025949	23823858	22935864	22923236	22824188	21582519
20159625	20055427	19996579	19792838	19721652	19679234	18896923	18793877
18352742	18175625	18074912	17934671	17096263	16834180	16603535	16220522
16091505	15989889	15890762	15710011	15674331	15572185	15448576	15305245
15094503	14914755	14497208	14403633	14384497	14383954	14300985	14299446
14207915	14178182	13860252	13637184	13332416	13322356	13152599	12956665
12932629	12535089	12530768	12337776	12219932	12152484	12017688	11842660
11826795	11620291	11322781	11277284	11225264	11011525	10962159	10758004
10674708	10629815	10273676	10250701	10241022	10165692	10129597	10025090
9779318	9623333	9505028	9479433	9478442	9407887	9396193	9369400
9338814	9068402	9061678	8840198	8831850	8793013	8717712	8706435

What can be solved?

Emoji = Emotion ?

Outline

1. Use cases and complexity of the problem

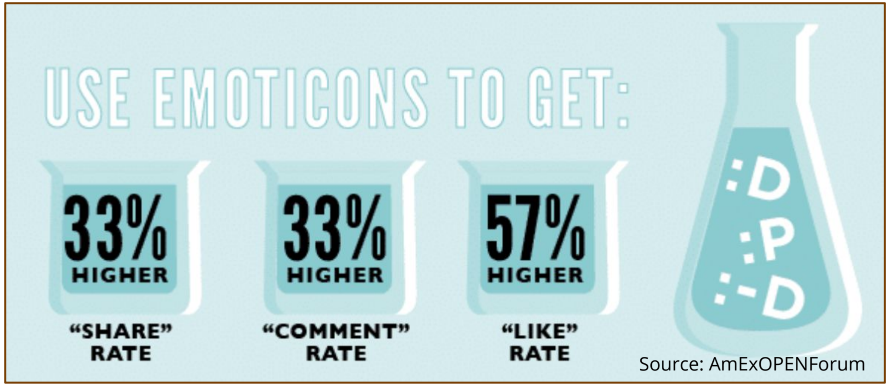
Methods

2. Dataset & Preprocessing
3. Multiclass vs Binary classification vs Personalization
4. Models
5. Evaluation

6. Conclusion
7. Future work

Why should we use emojis?

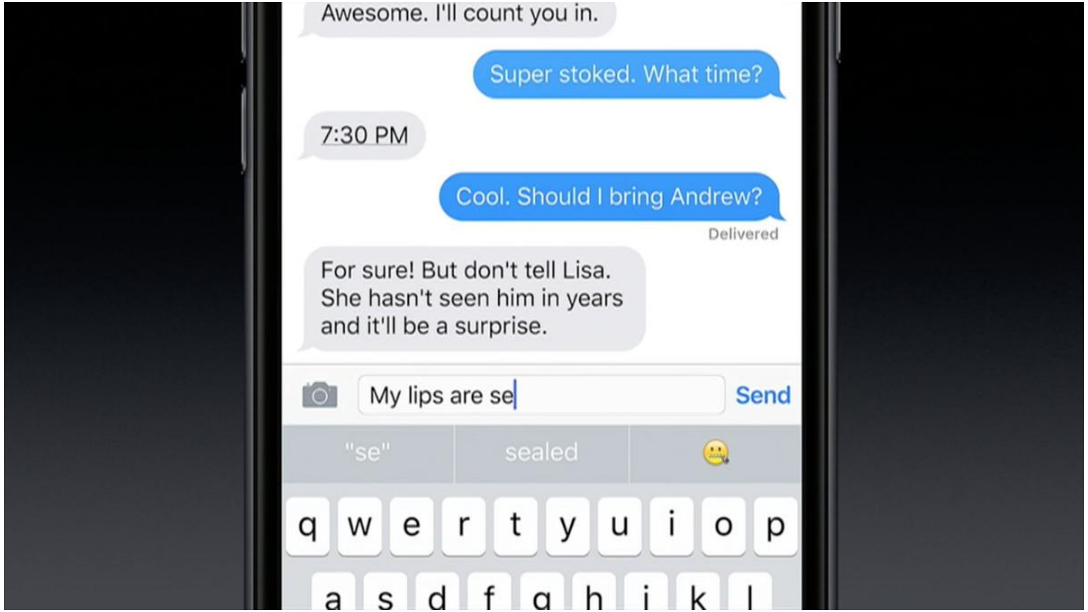
- *Makes it easier to express oneself*
- *Visual content is more likable*
- *Leads to better memorization*
- …

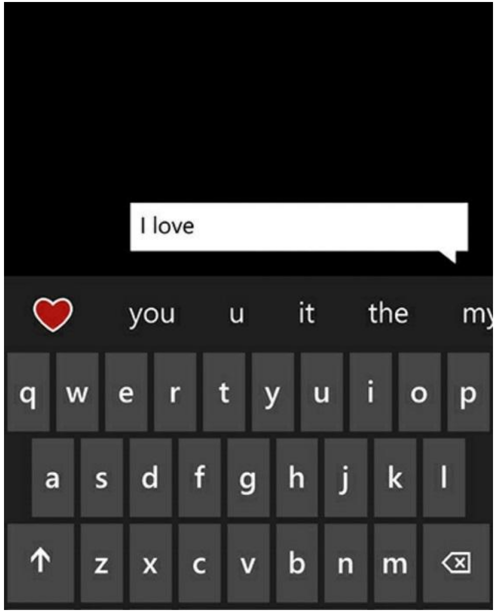


1. Emojis are used as an emotion or a word in a sentence.

“

Use Cases



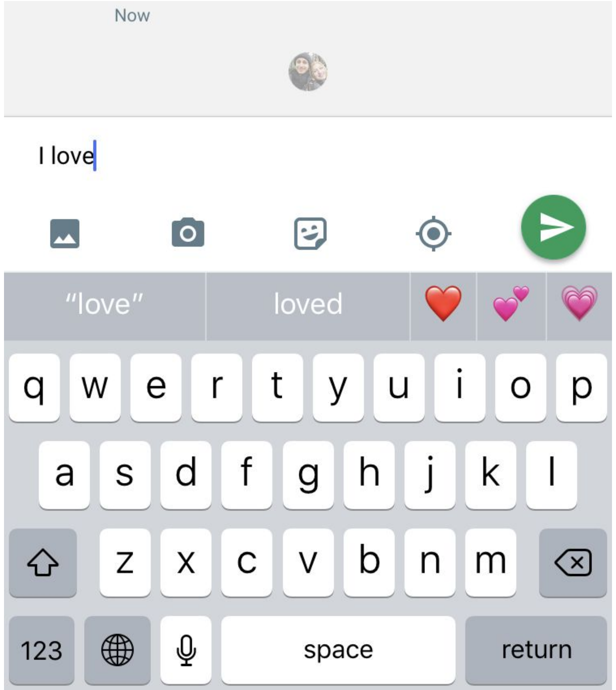


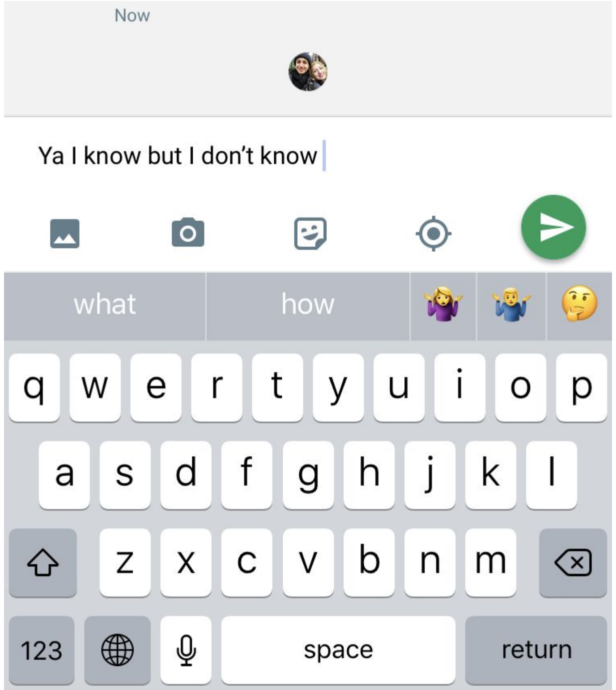
The idea:
Given the text that an user wrote, return top k emojis relevant to the text.

Goal

Upgrade from recommending up to 3 emojis and using n-grams.

“Existing system iOS





Problem Description

The original idea: Emoji Recommendations - Given the message/text that an user wrote, return top k emojis relevant to the text.

Problem:

What are the use cases?

Are emojis predictable?

Look at the tweets (with no emojis)

Guess what emoji describes the emotion of the text

Problem Description

Try guessing?

That's Alex!! I love her

 - ?

Problem Description

Try guessing?

That's Alex!! I love her

👱 - 😍

Problem Description

Try guessing?

You're right man, I just can't get hurt like that again

👱 - ?

Problem Description

Try guessing?

You're right man, I just can't get hurt like that again

🧑 - 😂

Problem Description

Try guessing?

You're right man, I just can't get hurt like that again

🧑 - 😂

Laughing to lighten the sentence.

Reverse Problem:

What does this emoji mean?

Reverse Problem:

What does this emoji mean?

expressionless face

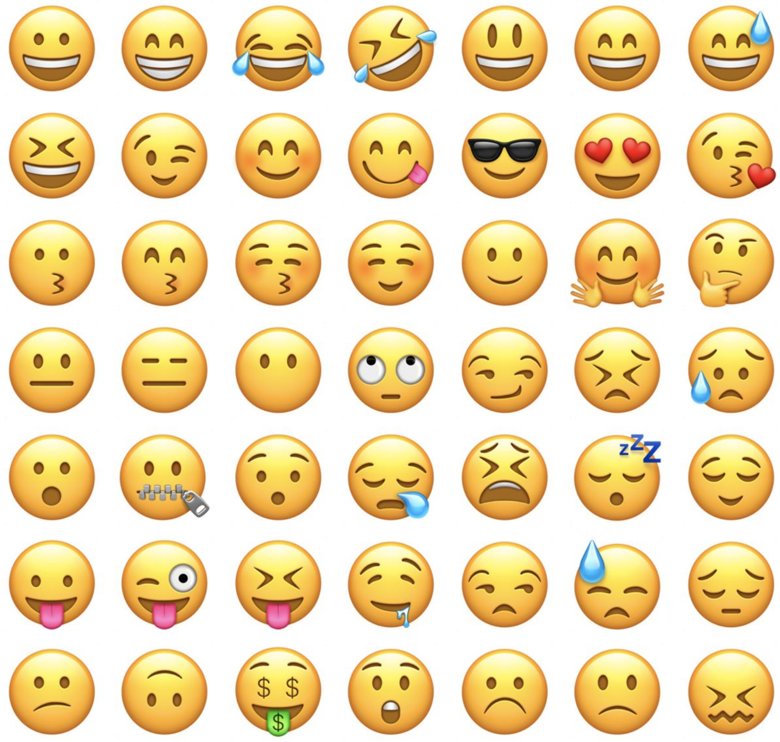
Neutral face

Reverse Problem:

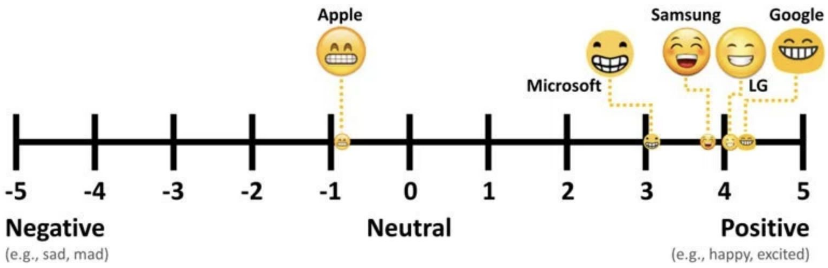
What does this emoji mean?
Or these ones?

- ***We educate ourselves in emojis***
- ***They are more ambiguous than words***

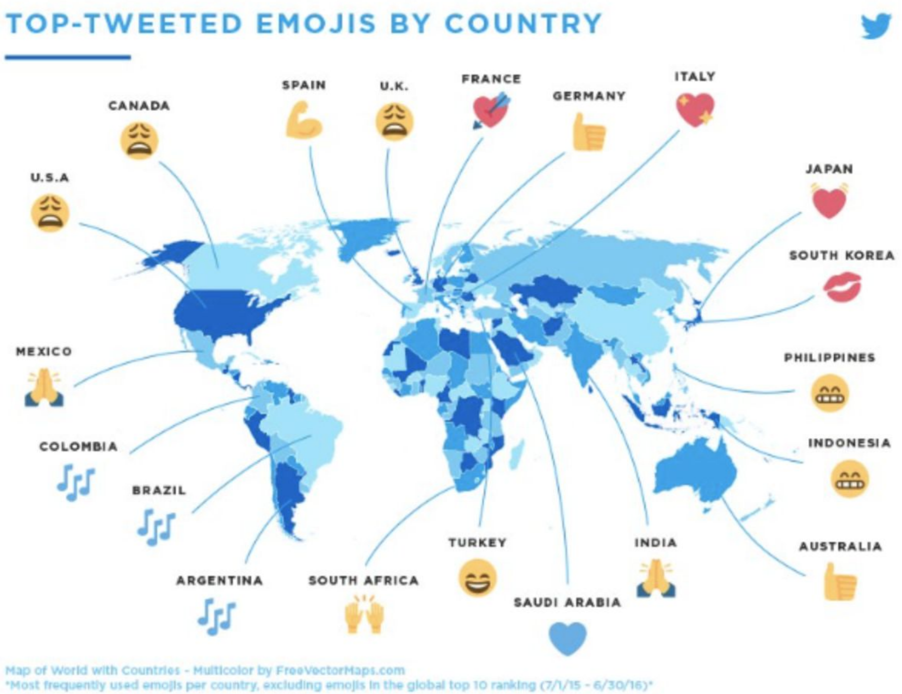
1 Emoji = 1 Emotion ?



- Emoji M:N Emotion
- Emoji usage can be can depend on culture, nationality, gender, age, social circle ...
- Emoji representations vary for different platforms



Miller at al. ICWSM-16



Complexity

There are 2753 in **v11.0β**

- *It is hard to find an emoji that you need*
- *There can be 2753+ labels for classification problem*

Emojis in a chat application can be used as:

- An answer to the previous text if it was a question,
- A reply for the previous text,
- A next word in the sentence.

Complexity

Emojis in any text can be used for:

- Expressing an emotion or a word.
- As a combination to describe:

a) **a phrase** - “☕🕒❓”- what time should we get coffee?

“👏 👏 👏👏👏”- go warriors.

b) **the strength of emotion** -

“ 😥😢😭” - very sad. “ 😂😂😂 “- very funny.

c) **any visual that has no separate emoji in the unicode yet.**

“ Every damn corner 🌮🚐 #TacoTuesday”.

“🐓🐔🐤🐥🐣” - life cycle.

🌆🏃 - city parkour.

😢🔫 - kill me now

20

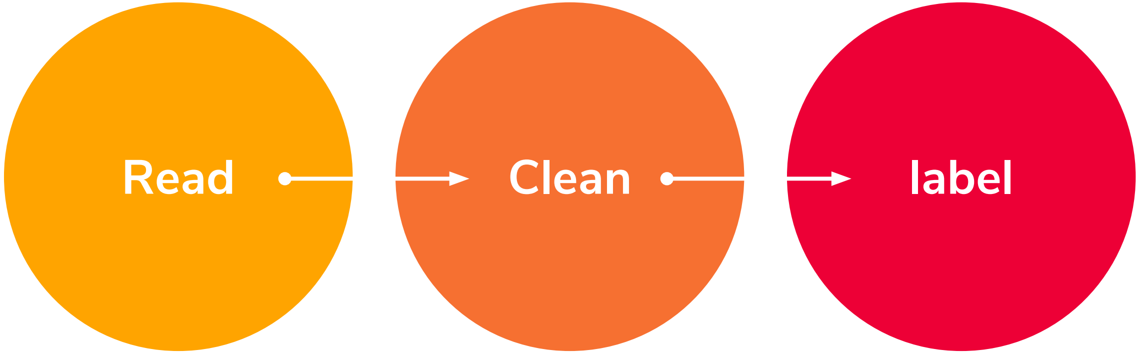
1.

Dataset & Preprocessing

Getting Tweets that include emojis

Dataset

- Twitter Streaming API - 1,560,000 tweets
  - Filters applied: Language = EN,
  - Emoji is in "**My emoji set**" (74)
- Personalized dataset 120,000 tweets(2) + 20,000 tweets(10)
- Cleaning: URL-s, spelling, #-s, words that contain numbers…
- Handling tweets with several emojis and combojis.
  - Add combojis as a label



Preprocessing

- Labeling:
  - The first emoji in the tweet
  - Yes / No
  - Separate entry for each emoji (not for combojis)
- Balancing the data
- Feature extraction - frequency of emojis, device, daytime...
- Encoding:
  - One Hot Encoding
  - Word Embeddings

Models

- MultiClass model*: General dataset classification for up to 60 labels
- Binary model - LSTM:
  - Create a binary classifier for each emoji on balanced data (5)
- Personalized model - LSTM:
  - Feature extraction - frequency of emojis, device, daytime...
  - Labels are only previously used emojis and combojis
  - Next word prediction using n-grams and stupid backoff
  - Mapping words to emojis
  - Scoring based on confidence (emoji frequency, model accuracy, predicted probability)

MultiClass vs Binary Classification vs Personalization

Change in Dataset / Change in Algorithm

Multi Class
vs
Binary

Complexity vs. Usability

Multi Class

1. More complex problem.
2. More data but…
3. How many emojis to use?
4. Which ones to use?
5. Does not work good with not frequent emojis.

Binary

1. Easier problem.
2. Introduces Bias & needs balancing.
3. Harder to detect with many choices of emojis with the same emotion.
4. Emoji choice is still limited

vs
Personalized

Complexity vs. Usability

Personalized

1. More complex problem.
2. Less data
3. More features
4. Less ambiguity
5. More emoji options
6. Suggesting new emojis (next word prediction)
7. Comboji support
8. ...

Implementation

NLTK

The preprocessing:

Word tokenizer

Training:

Naive Bayes Classifier

Scikit

Training:

Scikit classifiers:

Logistic Regression

Stochastic Gradient Descent

Keras on TensorFlow

Preprocessing:

Embedding Vector

Sequence

Training:

LSTM neural network

Evaluation

Evaluation Accuracy

Binary : 
365 000 tweets

60 Emojis
29%

20 Emojis
32%

Binary Classifier
71%

10 Emojis
39%

5 Emojis
52%

Evaluation Precision

Combined binary classifiers for 5 emoji P@1 - 73%

Barbieri et al. on Twitter dataset

General B-LSTM classifier with top 5 emojis - p@1 - 65%

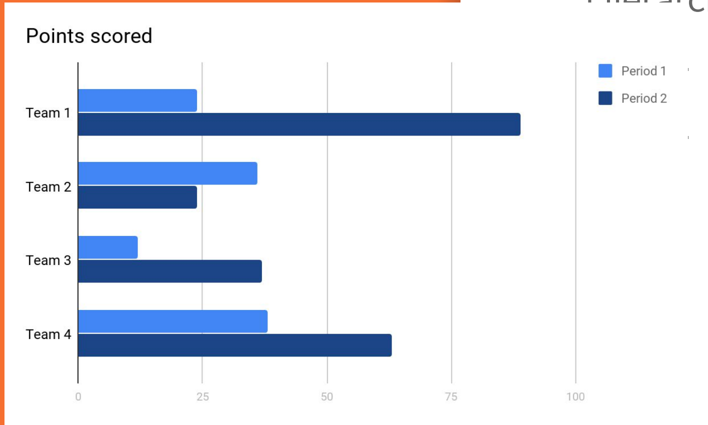
Human evaluation for the same was - 50%

Xie et al. on Weibo dataset

Hierarchical LSTM for understanding dialogue top 10 emojis

35%

65%



Different methods

Results, results...

Accuracy	5	10	20+
Naive Bayes	**48%**	**39%**	**32%**
Logistic Regression	**52%**	**38%**	**32%**
Stochastic Gradient Descent	**13%**	**9%**	**7%**

Evaluation
-
Precision

Next word prediction - 13.5%

LSTM model with additional features on personalized data (generated labels on average - 125):

P@1 - 61%

P@3 - 74%

LSTM with Next word prediction and scoring:

P@1 - 40%

P@3 - 34%

Maybe because there was not a recommender system...

“Alternative” way of evaluating the recommender system

Conclusion

Recommending emojis is a very complicated problem

It is fairly possible to break it down to subtasks - predict usage of one emoji.

Factors that help are:

Recommending several emojis from the same classifier

Using additional features about user

Using personalized data

Future Work

Future Work

Dataset

Collect Facebook data for using more features

Recruit people

Real world experiment

Human Evaluation

Volunteers? ;)

Resources

For the idea…

- **Analyzing Twitter Sentiment of the 2016 Presidential Candidates** by Delenn Chin, Anna Zappone, Jessica Zhao
- **Emotional Chatting Machine: Emotional Conversation Generation with Internal and External Memory** by Hao Zhou, Minlie Huang, Tianyang Zhang, Xiaoyan Zhu, Bing Liu
- **Are Emojis Predictable?** By Francesco Barbieri, Miguel Ballesteros, Horacio Saggion
- … etc

Thanks to:

Dr. Lipyeow Lim and Dr. David Chin

for guidance

Ed White and Gene Park

for donating their tweets

Nicolas Golubovic, Muzamil Yahia, Mark Nelson and Takumi Aoki

for friendly support and reviewing my work

That was all

It’s freezing here

Thanks for listening

Do you have any Questions?