

Emoji Prediction for Text Messages

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Outline

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Introduction

Motivation

- In addition to the widely used auto correction for texts and prediction of next words (i.e SwiftKey) propose also Emoji Predictions
- Usage of larger Dataset including generate labeling (based on Emojis)
 - Search for multidimensional sentiment labels (instead of positive to negative)
 - Usage of Emojis are related to topics occurring in text message, as well as to the writers sentiment

Topic vs Sentiment Emojis

Topic 

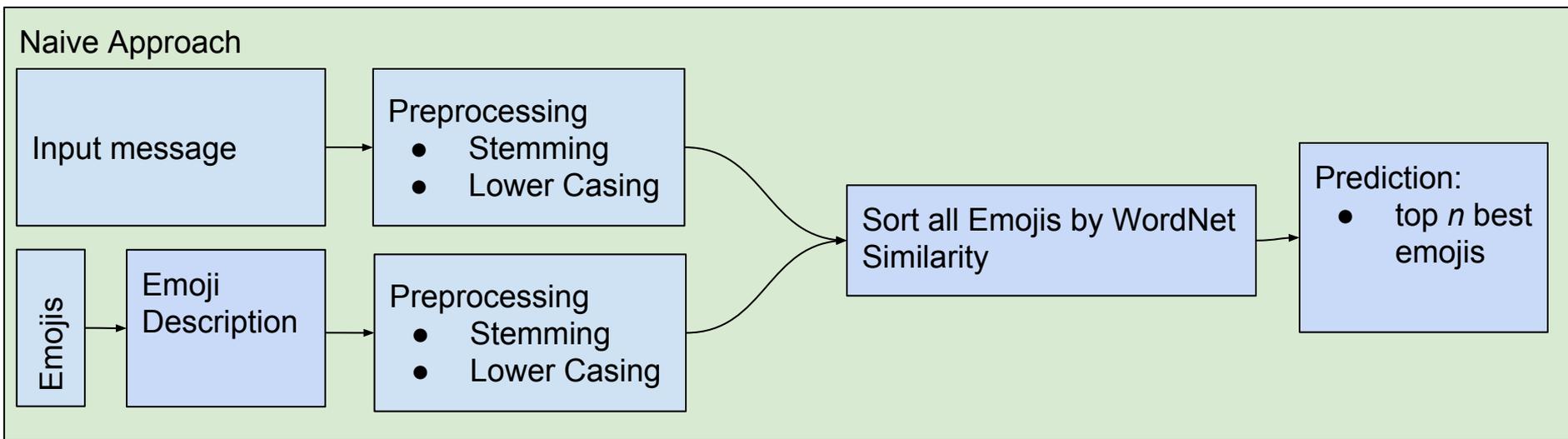
- close to occurring words in text
- less interpretation

Sentiment 

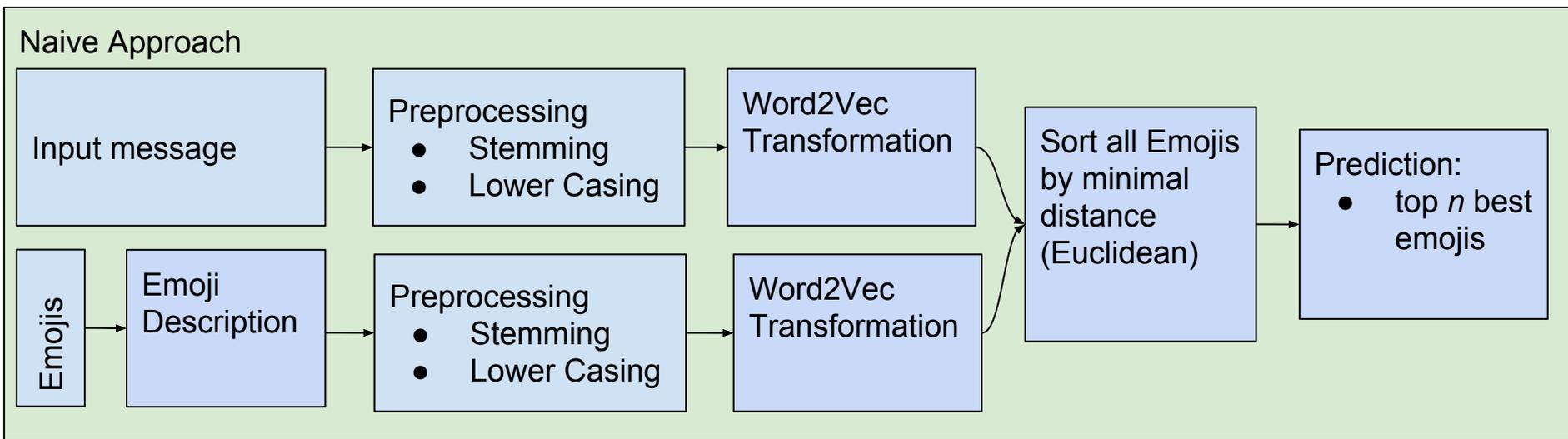
- not easy to interpret sentiment directly from text
- need of intelligence
- Machine learning and mining of text messages

Naive Approach

Naive Approach - Wordnet (slow)



Naive Approach - Word2Vec



Naive Approach

- Emoji Specifications (see [4])

Emoji	Specifications
	BIRTHDAY CAKE
	HIGH-SPEED TRAIN
	FACE WITH ROLLING EYES

- Transform message to vector representation
- Matching by similarity or closest distance
- Effective for topic-related emojis
- Not good for emotion-related emojis (too complex)
- Development of Advanced Approach

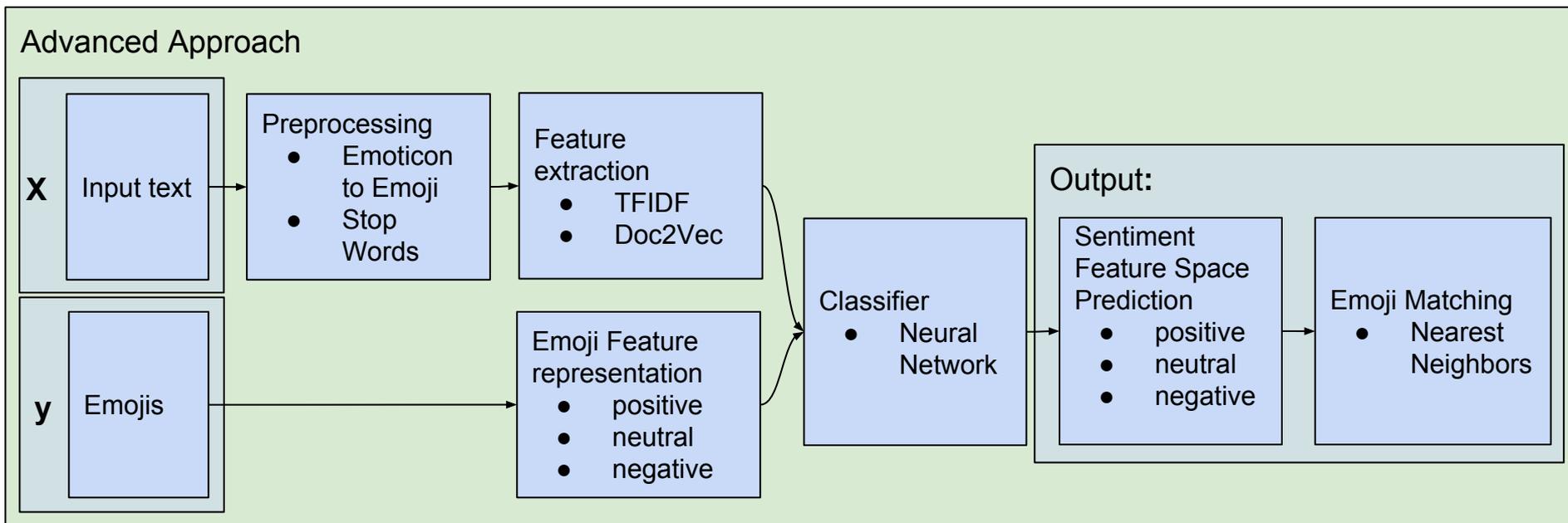
WordNet vs. Word2Vec & Distance

- WordNet
 - built in Similarity function
 - used on message words and all word in specifications
 - old Naive Approach (more intuitive similarity)
- Word2Vec & Distance
 - Vector Embedding of each Word
 - pairwise Euclidean distance of words in message and emoji specifications

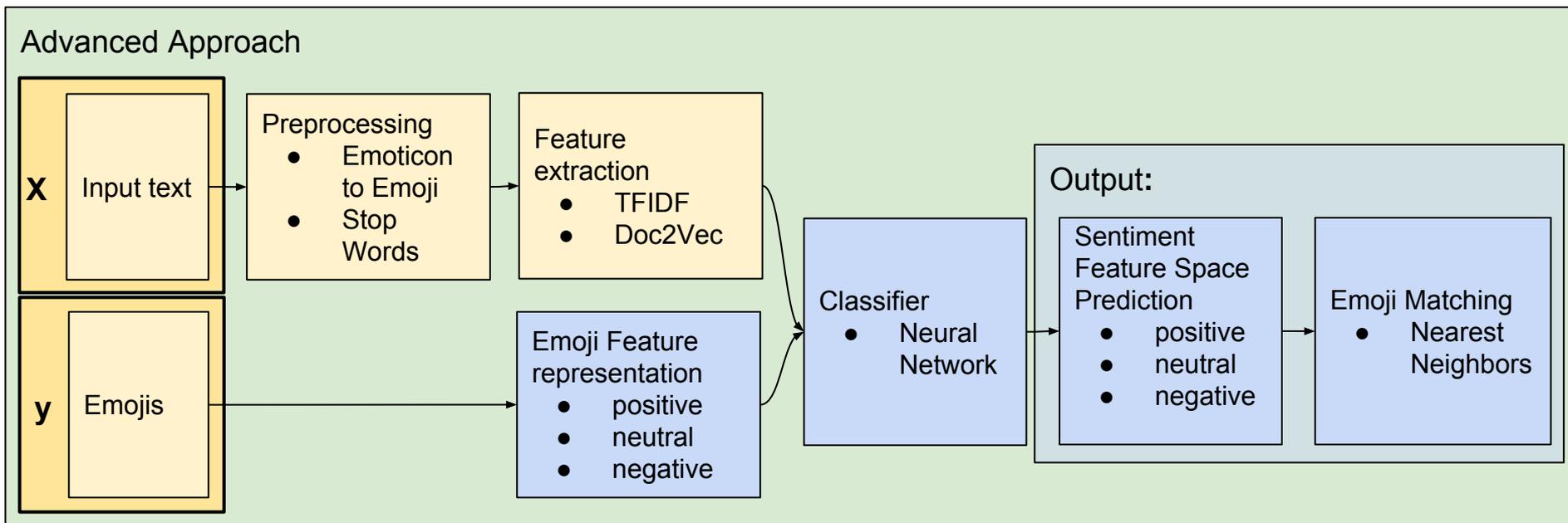
→ we use “WordNet” because it performs better

Advanced Approach

Advanced Approach Outline



Advanced Approach Outline



Twitter Data to Feature Representation

Workflow

DATA

- Twitter Data
 - + Huge Dataset
 - + Interesting for Mining for Sentiment Analysis
 - + Broad Usage of Emojis
 - - No true Labelings → have to construct our own based on Emojis
- Split each message into text as X and sentiment representation of emojis as y
 - also store metadata for additional input (see outlook)
- use emojis as sentiment label
 - accepting noise

Feature extraction

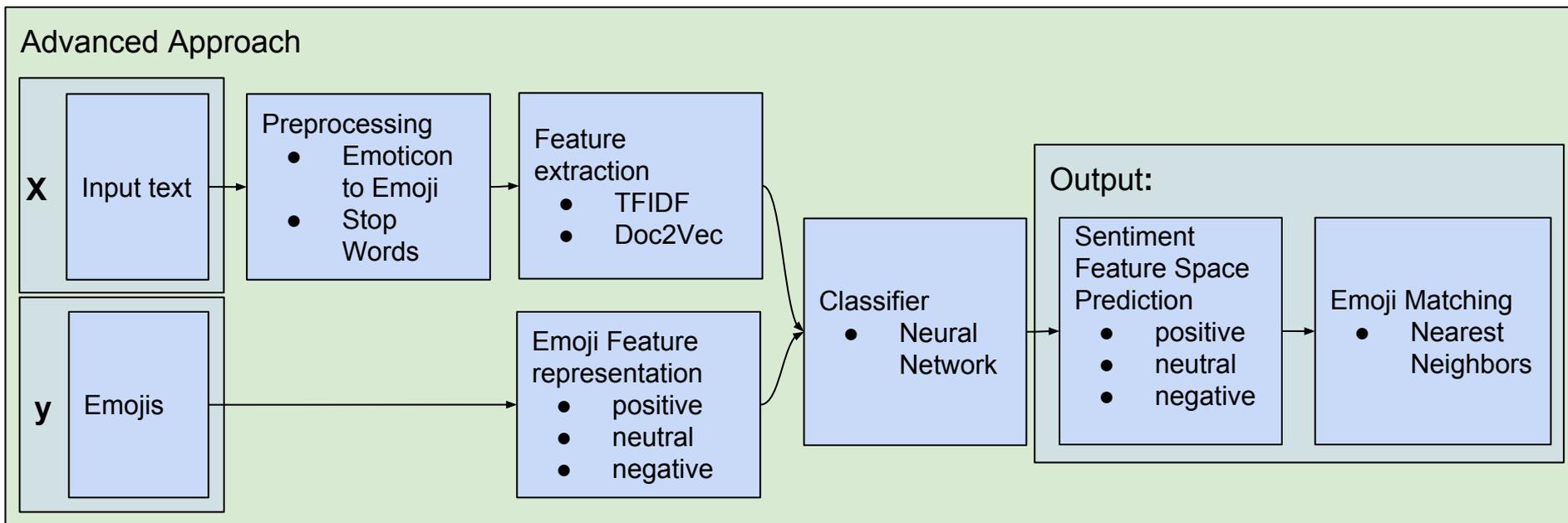
TFIDF

- Relative frequency of terms (TF), weighted by inverse document frequency (IDF)

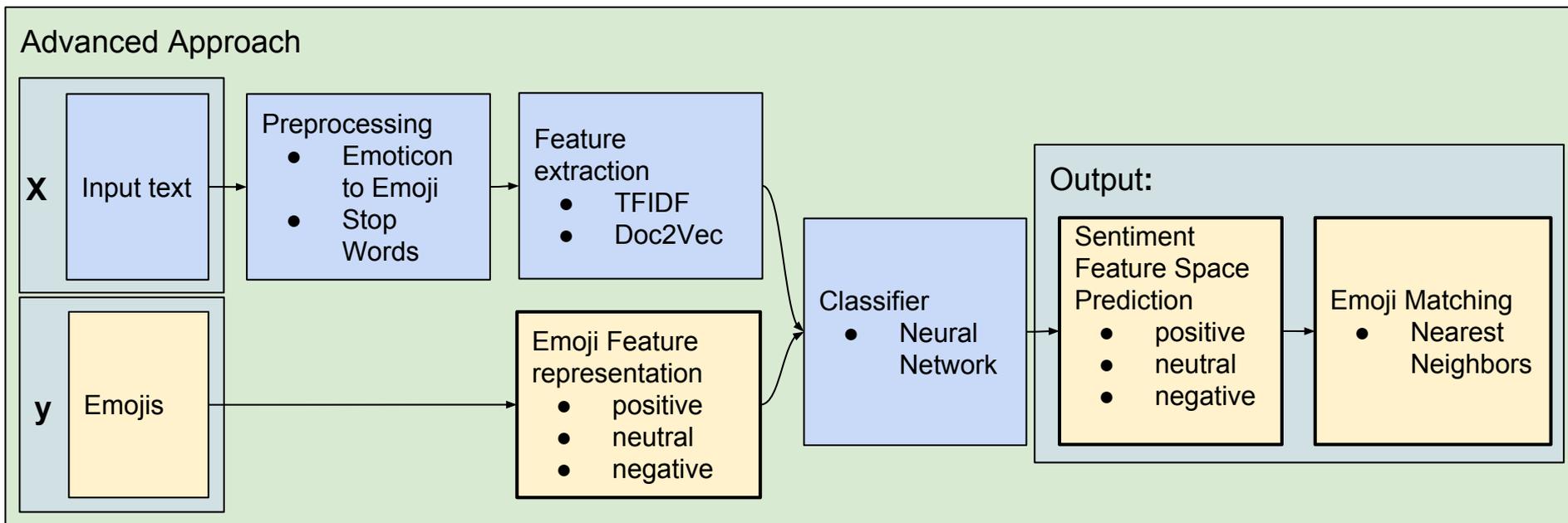
Doc2Vec

- Feature representation of words, based on their semantic similarity
- Additional vector for each document (message)

Advanced Approach Outline



Advanced Approach Outline



Sentiment Space

Emoji Representation

- 3-dimensional feature space
- The vector entries correspond to the relative occurrence of the emoji in different contexts [2].
- The possible contexts are “Positive”, “Negative” and “Neutral”.

Emoji/ Sentiment			
positive	0.27	0.75	0.16
negative	0.48	0.05	0.56
neutral	0.25	0.19	0.28

Emoji Neighborhood

- Using the 3-dimensional vector representation
- Error function:
 - Euclidean distance of the prediction to the correct outcome in the feature space.

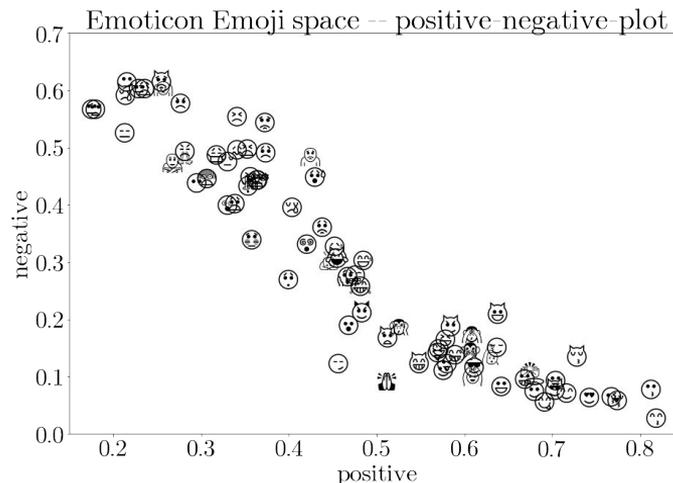
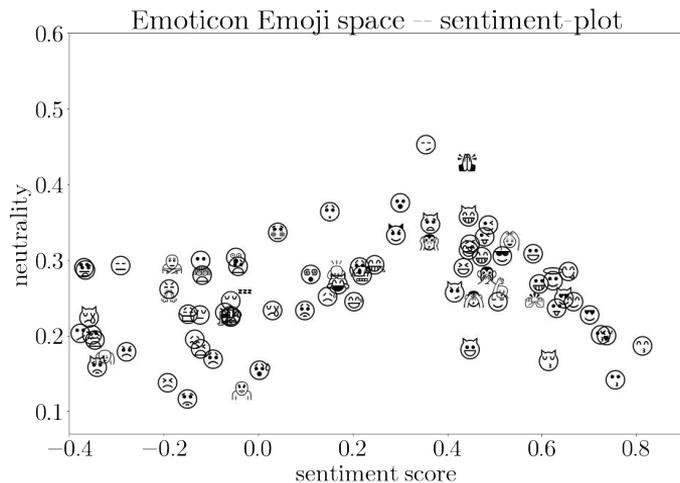
→ Regression Problem

Distances example:

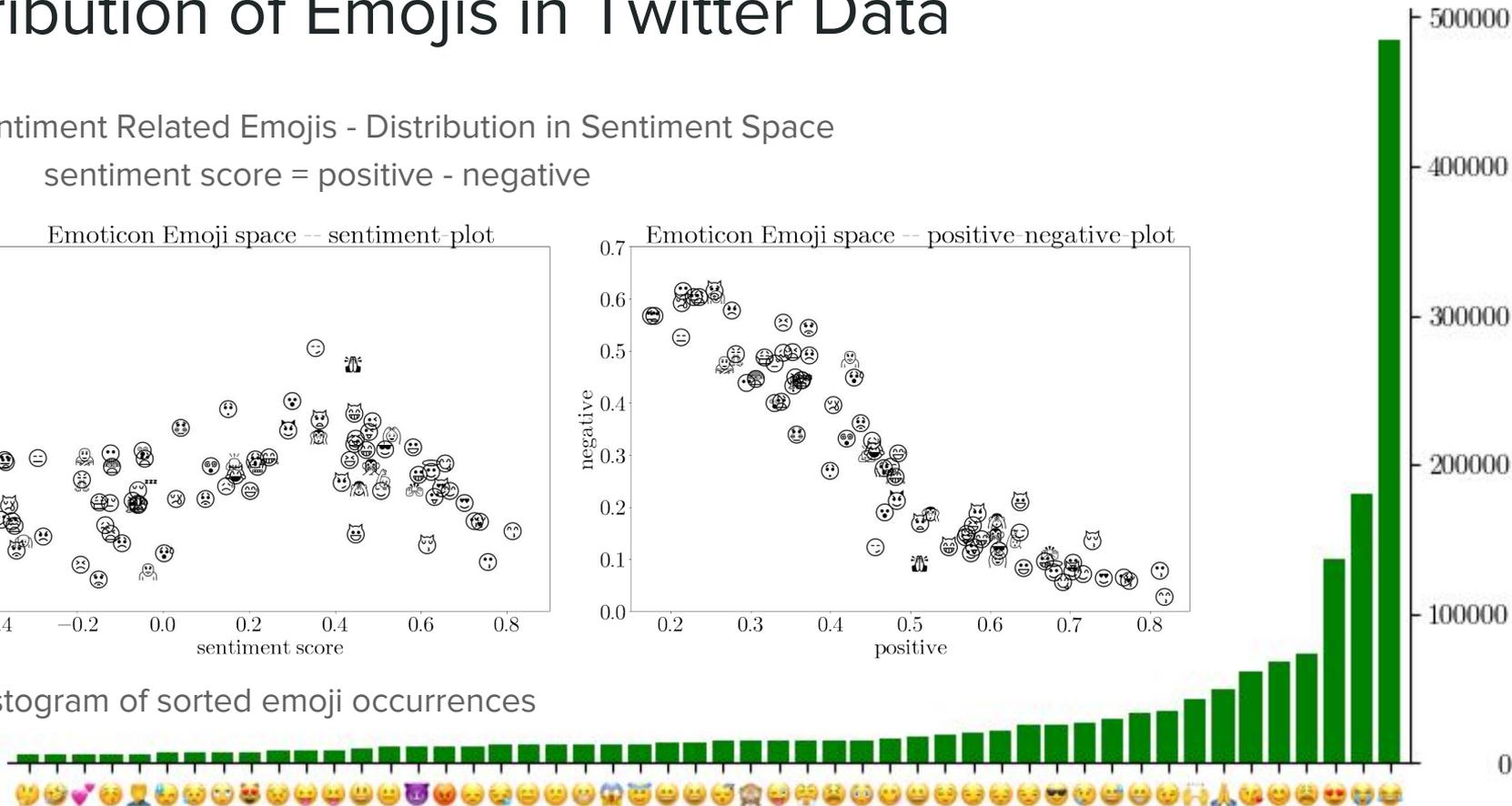
Emoji	Neighborhood
	      
	      

Distribution of Emojis in Twitter Data

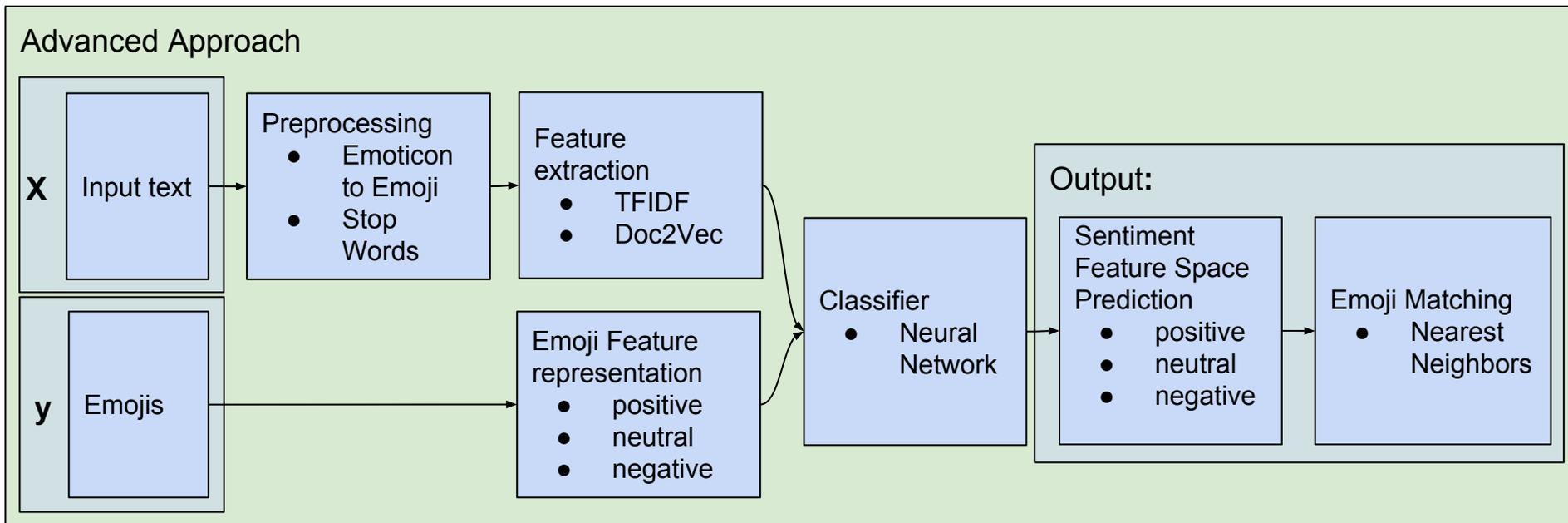
- Sentiment Related Emojis - Distribution in Sentiment Space
 - sentiment score = positive - negative



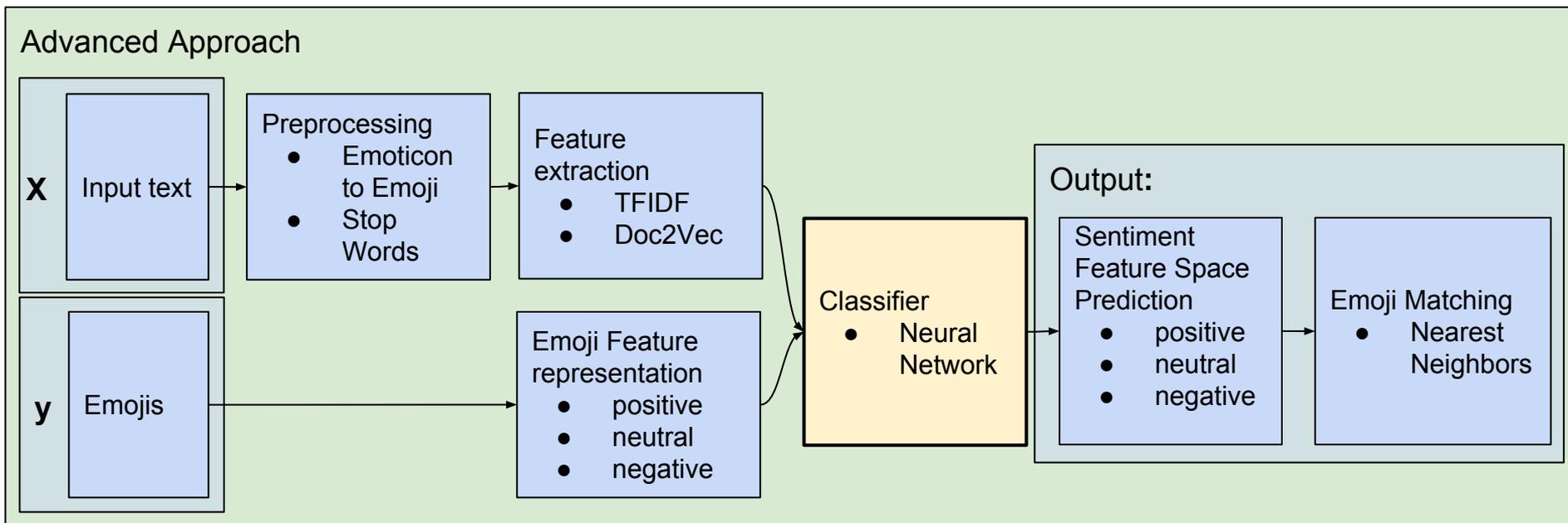
- Histogram of sorted emoji occurrences



Advanced Approach Outline



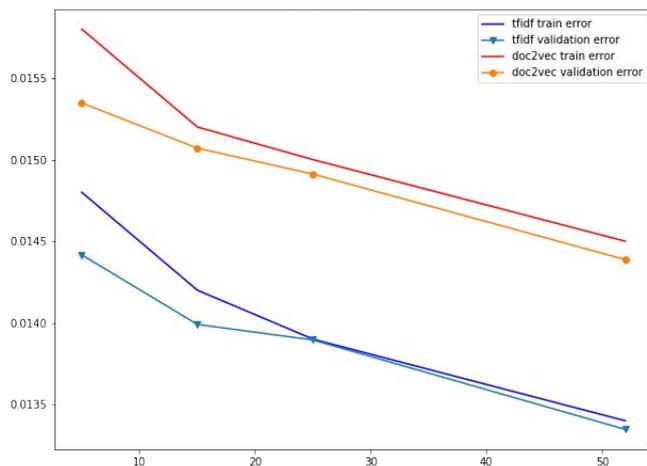
Advanced Approach Outline



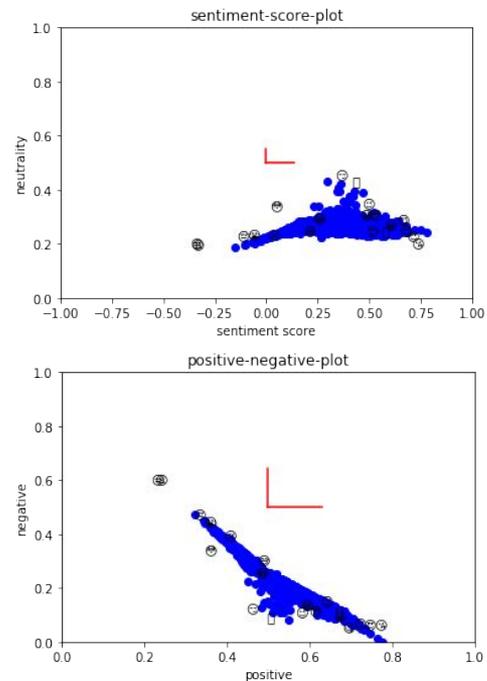
Training and Evaluation

Parameter

- training over 52 datasets
 - 1 Million messages used for training
- 3 hidden layers
- doc2vec vs. TFIDF

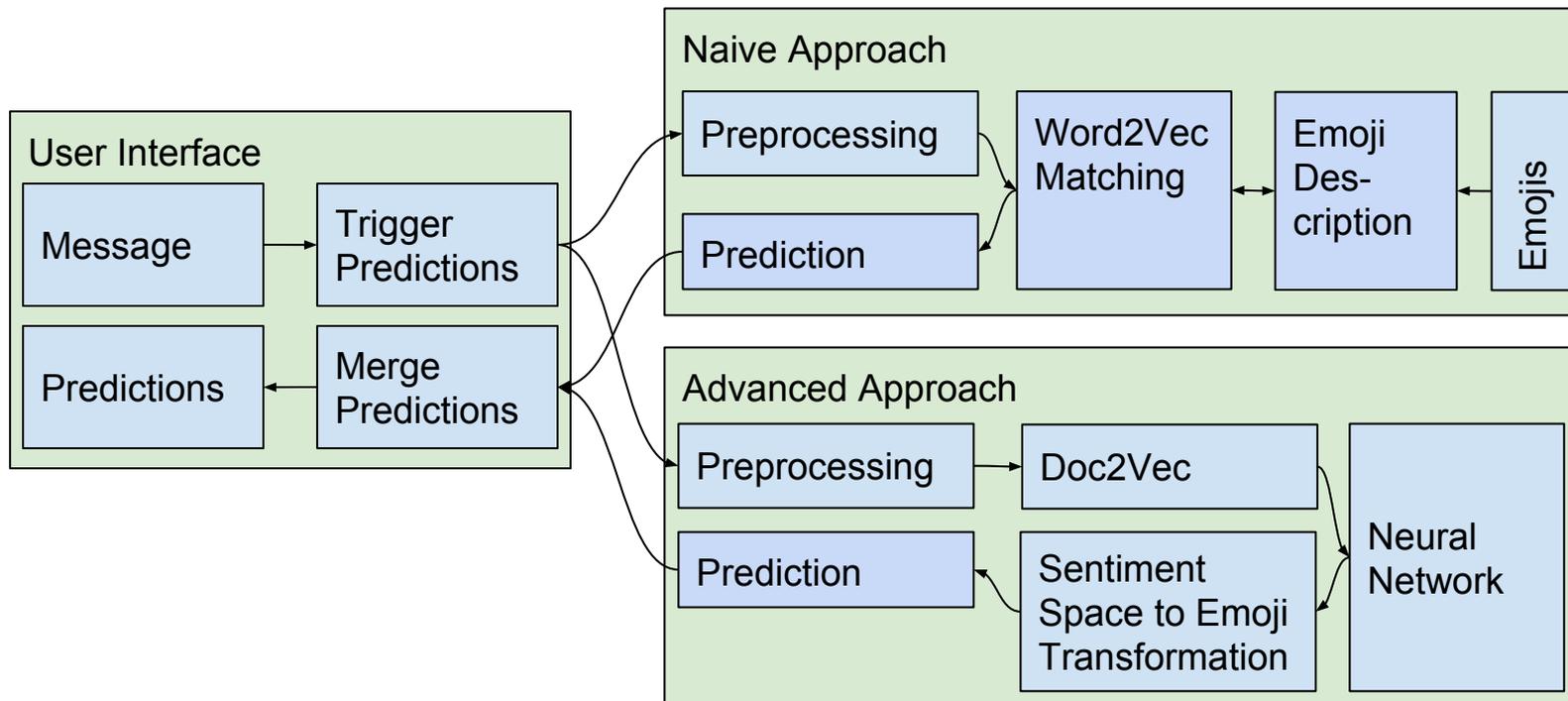


TFIDF plot validation set:



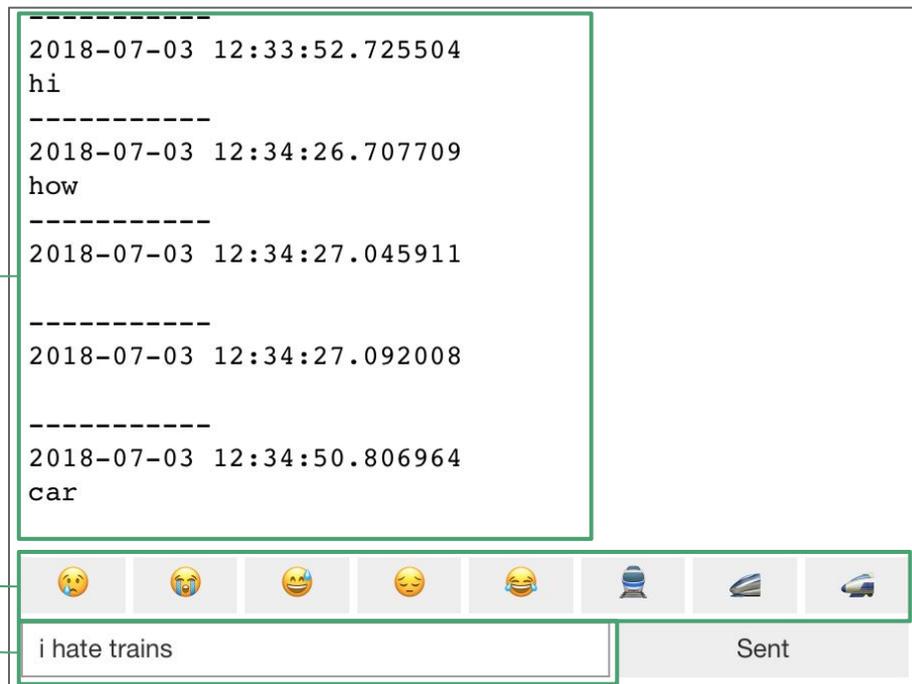
Merged Approach

Merged Approach - Design



User Interface

- Implemented for interactive Hands On
- Using Jupyter widgets to have opportunity to offer buttons labeled with predictions
 - also for potential reinforcement learning (see *outlook*)
- Components
 - Chat History
 - Sentiment & Topic related
 - 8 Predictions (usual 50/50 split)
 - Message Input



The screenshot displays a chat interface with a chat history and a message input field. The chat history shows four messages with timestamps and predicted words:

```
2018-07-03 12:33:52.725504  
hi  
-----  
2018-07-03 12:34:26.707709  
how  
-----  
2018-07-03 12:34:27.045911  
-----  
2018-07-03 12:34:27.092008  
-----  
2018-07-03 12:34:50.806964  
car
```

Below the chat history is a message input field containing the text "i hate trains" and a "Sent" button. Above the input field is a row of eight buttons, each with an emoji: a sad face, a crying face, a face with a sweat drop, a face with a neutral expression, a face with a wide smile, a train, a train, and a train.

Discussion and Evaluation

Limitations and Problems

Dataset (Twitter Data)

- easy and free access
- no true labeling
 - have to use emoji as labeling
- few dialogues with deep emotions but bashing, sarcasm
 - emoji usage less likely to lead to a sentiment labeling

Emoji-Sentiment Representation (see [Advanced Approach](#))

- Sentiment space → continuous labeling
- only 3 dimensions (very rough approximation of true sentiment)
 - Usage based on access to data for emoji to sentiment transformation
- but all in all not developed or improved on our own

Limitations and Problems - Evaluation

Evaluation - Metric

- Prediction based on regression so continuous results
 - but not so intuitive whether prediction is good or bad
 - error based on our NN or on the used sentiment space
- Idea of emoji clustering as a smooth multiclass evaluation
 - k-means clustering on the top 20 most used emojis
 - k = 5 yields meaningful clusters
 - could be used as an alternative performance measure
 - check if the regression result lies in the correct cluster
 - more interpretable than mean squared error
 - but not an exact measure

1: ['😭', '😓']

2: ['😞', '😔']

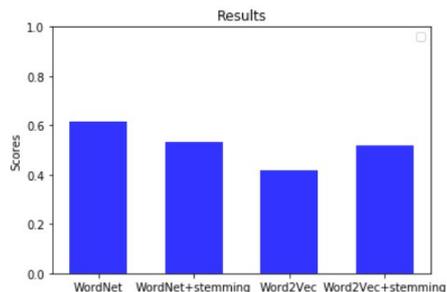
3: ['🙏', '😊', '😄', '😎', '😌', '😏']

4: ['😭', '😢', '😓', '😡']

5: ['😍', '😘', '😗', '👏', '😜', '😃']

Limitations and Problems - Evaluation

- Alternative Evaluation on 120 sentences
 - as validation data
 - designed to have a true labeling
 - 60 sentences topic, 60 sents sentiment
- Topic related
 - Compared different Vectorizers
 - Wordnet, Word2Vec, Stemming (on/off)



- Sentiment related
 - Compared different Vectorizers
 - TFIDF (acc = 85%), Doc2Vec (acc = 60%)

Examples

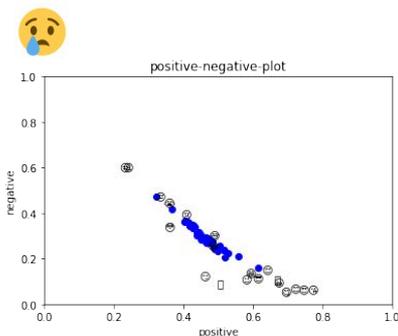
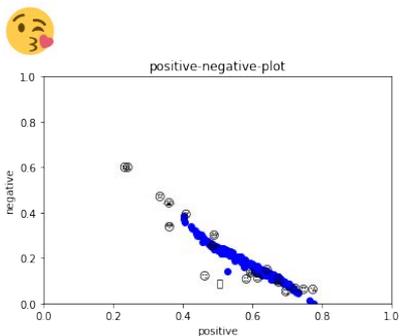
Topic Related	sentence	prediction
good examples	would you kiss a frog to get your prince	👉😬😬😬👑🍷🍷👗🌹
	what a beautiful dress	👉😬😬😬😬😬😬👗
	do you ever climbed a mountain	😬😬😬😬😬🚠🚲🏔️🏠
bad example	let's go out in a bar tonight	😬😬😬😬😬📺📺📺📺📺

Sentiment Related	sentence	prediction
good examples	I hate school	😬😬😬😬😬😬😬📺📺📺📺
	I am so happy	😬😬😬😬😬😬😬👉😬😬😬😬😬😬
	you are my best friend ever	😬😬😬😬😬😬😬😬😬😬😬😬😬
bad example	I want to dance and sing aloud	😬😬😬😬😬😬😬😬😬😬😬😬😬

Results in Sentiment Space

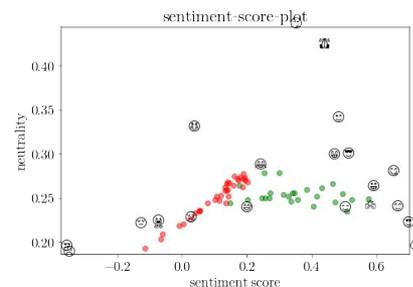
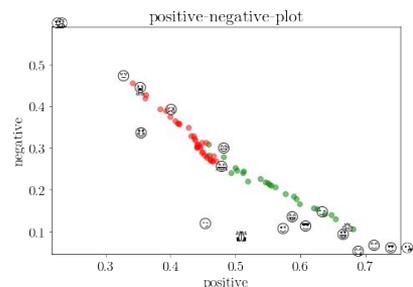
Twitter Data

- Overall performance: still a little bit random.
- E.g. compare prediction of messages labeled with the following emojis:



Validation Data (60 sentiment sentences)

- better prediction with same classifier on messages with strong emotional content.
- result on hand labeled messages:
 - (green = positive, red = negative)



Outlook

Reinforcement Learning

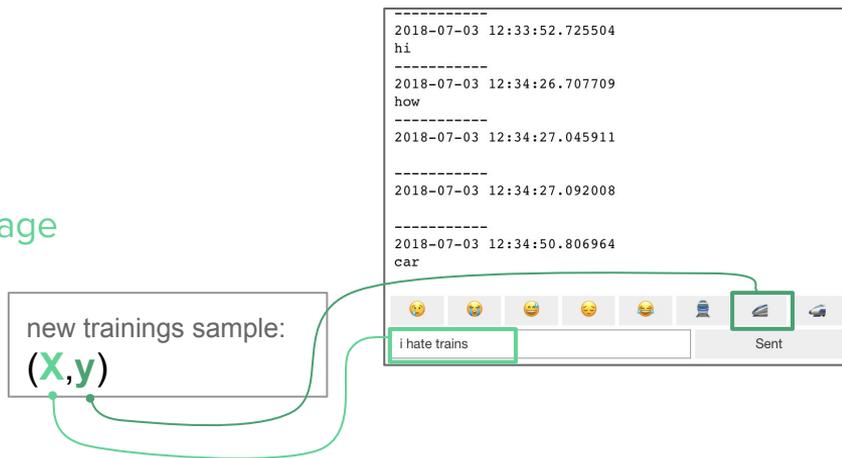
- generate training samples from usage of UI by taking **clicked emoticon** as training-label for **written textmessage** to improve our prediction online

Metadata as Additional Input

- Dialog dependent prediction
 - better personalisation of predicted emojis (based on Overall/Dialog/Individual Usage)

Multi Language

- currently only english



References

References

- [1] Hallsmar, F. and Palm, J.: *Multi-class Sentiment Classification on Twitter using an Emoji Training Heuristic*, KTH Royal Institute of Technology, Stockholm 2016.
- [2] Novak, P.K.; Smailovic, J.; Sluban, B. and Mozetic, I.: *Sentiment of Emojis* (Journal Paper), PLoS ONE 2015.
- [3] Zhao, L. and Zeng, C.: *Using Neural Networks to Predict Emoji Usage from Twitter Data*, Stanford University, 2017.
- [4] Emoji specifications: <https://unicode.org/emoji/charts/full-emoji-list.html>.

Thank you for your attention!
