Universität Stuttgart
Institut für
Maschinelle Sprachverarbeitung

Computational Natural Language Understanding: Use cases in the life sciences and psychology

Inaugural Lecture

November 13, 2020

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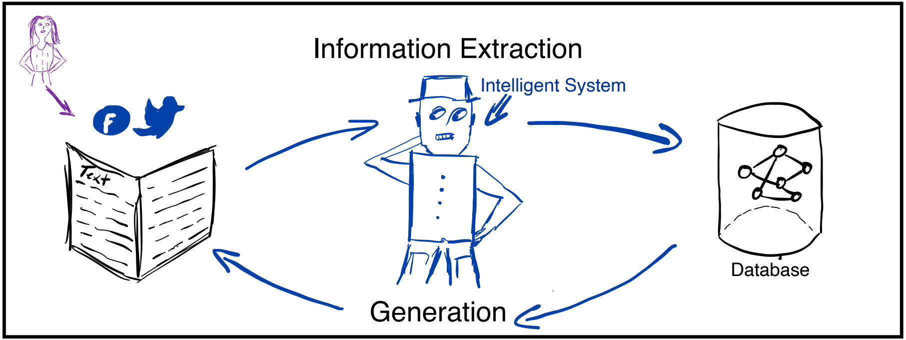
About Myself (and Stuttgart)

- 1999–2006: Studies at University of Dortmund:
  Computer science with minor psychology
- 2006–2010: Doctoral studies at Fraunhofer SCAI, St. Augustin:
  Biomedical text mining, machine learning
- 2010, 2013: Research visits at UMass Amherst:
  Probabilistic machine learning, MCMC inference
- 2011–2012: Postdoc at Fraunhofer SCAI:
  Social media mining, eGovernment
- 2013–2014: Postdoc at Bielefeld University:
  Sentiment analysis, opinion mining
- 2015: Co-Founder of Semalytix GmbH (exit 2020)
- 2014–2015: Visiting professor at Uni Stuttgart
- 2015–: (Senior) Lecturer at IMS
- 2020: Habilitation in Computer Science:
  Structured Modelling of Affect in Text

Outline

Language Understanding

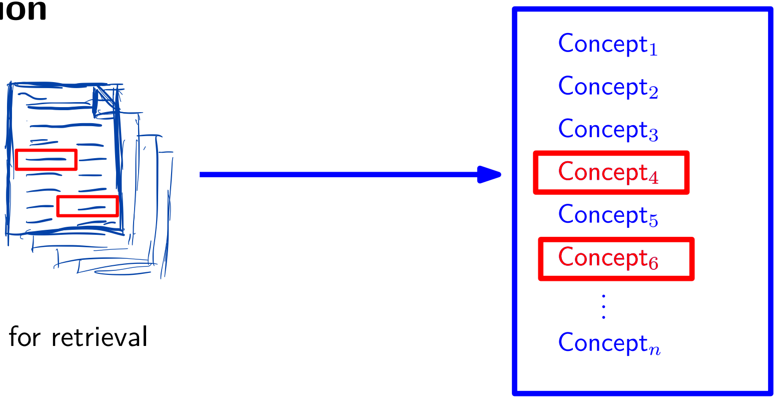


- Challenges:
  1. Interpret and structure propositional knowledge/statements
  2. Infer properties about author of message
- Two case-studies: Biomedical Information Extraction and Emotion Analysis

Goal of this lecture

- Outline approaches to information extraction, highlight particularities of biomedical NLP and emotion analysis
- Highlight differences between text genres/domains and particular challenges
- Discuss methodological implications for extraction tasks of different types
- I'll let you know at the end how these clearly very different topics can come together in applications.

Concept Identification



- Identify concept: sufficient for retrieval
- Identify mention position:
  nice to have for further analysis tasks
- Multiple concepts can be associated with one document
- (I am mixing NER, Entity Linking, and Document Classification here.)

Outline

BioNLP and Medical NLP

- Automatically extract information from texts in the life science domain
- A lot of information is hidden in text.
  - Scientific papers (from PubMed)
  - Discharge letters
  - Documentations of clinical trials
- Entity classes of interest:
  - Gene/names, mutations, species
  - Chemical compounds, drugs, treatments
  - Diseases, medical conditions, adverse effects
  - ...

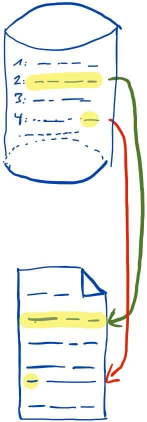
Example: How to find drug names and chemical compounds?

Idea:

- Let's check for existing data bases
- Implement a (fuzzy) dictionary-matching algorithm

⇒ Find mentions and link to databases in one step

⇒ Directly find chemical compound



Chemical Names: Terminological Resources and Corpora Annotation

Corinna Kolářik*†, Roman Klinger†,
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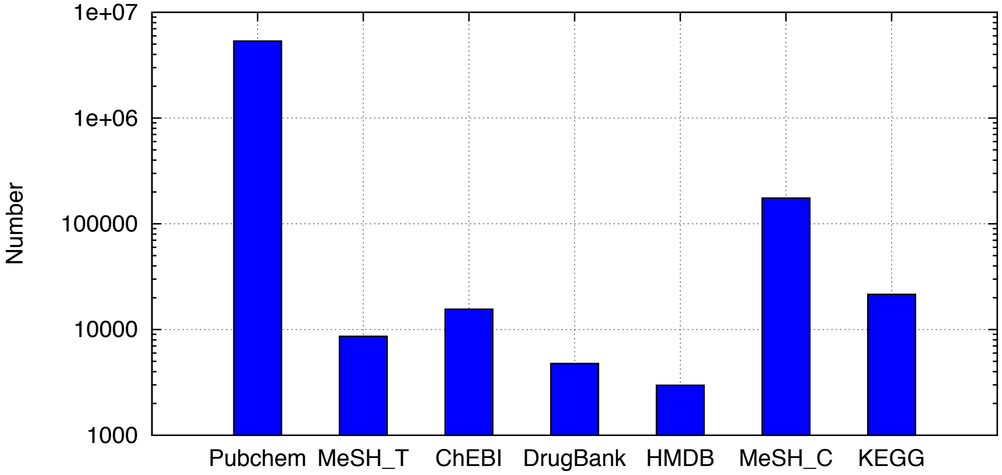
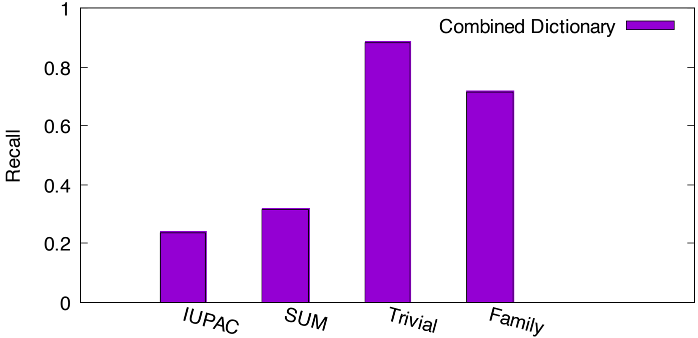
Chemical compound databases: Size



Chemical compound databases: Recall on annotated corpus



- But: 0.13 Precision.

Example results

DEPARTMENTS: NURSING AND THE ARTS

Empowering Women Since 1912: The Girl Scouts of America

YOUNG-MASON, JEANINE EdD, RN, CS, FAAN

Section Editor(s): Young-Mason, Jeanine EdD, RN, CS, FAAN **Author Information**

Clinical Nurse Specialist: July/August 2012 - Volume 26 - Issue 4 - p 227-228
doi: 10.1097/NUR.0b013e31825aea30

Clin Exp Immunol. 2019 Apr; 196(1): 28–38. PMCID: PMC6422647
Published online 2019 Feb 27. doi: 10.1111/cei.13265 PMID: 30697704

Exploring immunomodulation by endocrine changes in Lady Windermere syndrome

M. R. Holt,[1,2] J. J. Miles,[3] W. J. Inder,[1,4] and R. M. Thomson[1,2]

Review > Res Microbiol. 2015 Dec;166(10):782-95. doi: 10.1016/j.resmic.2015.09.002. Epub 2015 Sep 25.

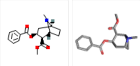
Snow and ice ecosystems: not so extreme

Lorrie Maccario[1], Laura Sanguino[1], Timothy M Vogel[1], Catherine Larose[2]

Affiliations + expand

PMID: 26408452 DOI: 10.1016/j.resmic.2015.09.002

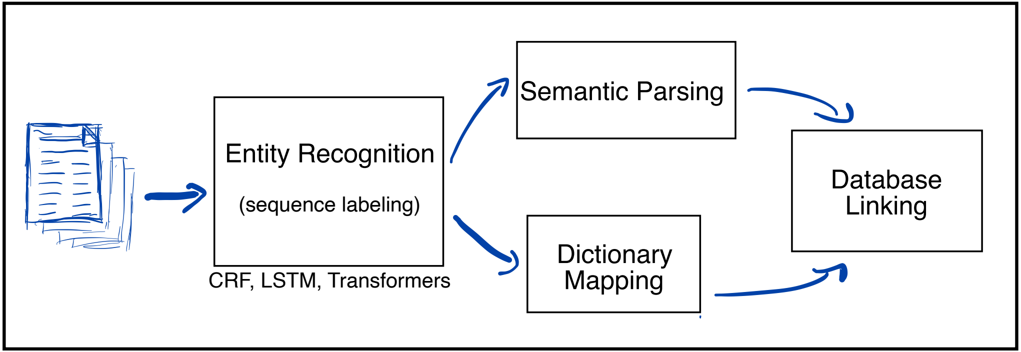
Cocaine

PubChem CID:	446220
Structure:	 2D 3D Find Similar Structures
Chemical Safety:	 Acute Toxic Irritant Laboratory Chemical Safety Summary (LCSS) Datasheet
Molecular Formula:	$C_{17}H_{21}NO_4$
Synonyms:	cocaine Kokain Neurocaine Cocain L-Cocaine More...

Cocaine Synonyms

cocaine Kokain Neurocaine Cocain L-Cocaine Cocaina beta-Cocain (-)-Cocaine Methyl Benzoylecgonine l-Cocain Benzoylmethylecgonine Leaf Dama blanca Pimp's drug Cocaine free base 1-Cocaine White girl or lady cocainum Star-spangled powder Cocaine, l- Eritroxilina Erytroxylin Kokayeen Bernies Burese Corine 50-36-2 Kokan Coke UNII-I5Y540LHVR Bernice Cholly Cecil Flake Blow Girl Lady Rock Snow Toot Happy trails Green gold Happy dust Nose candy Gold dust Star dust CHEBI:27958 2-beta-Carbomethoxy-3-beta-benzoxytropane HSDB 6469 C"Carrie I5Y540LHVR 2-beta-Tropanecarboxylic acid, 3-beta-hydroxy-, methyl ester, benzoate (ester) methyl (1R,2R,3S,5S)-3-(benzoyloxy)-8-methyl-8-azabicyclo[3.2.1]octane-2-carboxylate Crack cocaine Methyl 3beta-hydroxy-1alphaH,5alphaH-tropane-2beta-carboxylate benzoate (ester) COC Ecgonine, methyl ester, benzoate (ester) Jam Crack 3-Tropanylbenzoate-2-carboxylic acid methyl ester 2beta-Carbomethoxy-3beta-benzoxytropane 1-alpha-H,5-alpha-H-Tropane-2-beta-carboxylic acid, 3-beta-hydroxy-, methyl ester, benzoate 2-Methyl-3beta-hydroxy-1alphaH,5alphaH-tropane-2beta-carboxylate benzoate (ester) 3-(Benzoyloxy)-8-methyl-8-azabicyclo-(3.2.1)octane-2-carboxylic acid methyl ether 3beta-Hydroxy-1alphaH,5alphaH-tropane-2beta-carboxylic acid methyl ester benzoate methyl (1S,3S,4R,5R)-3-benzoyloxy-8-methyl-8-azabicyclo[3.2.1]octane-4-carboxylate methyl [1R-(exo,exo)]-3-(benzoyloxy)-8-methyl-8-azabicyclo[3.2.1]octane-2-carboxylate Methyl 3-beta-hydroxy-1-alpha-H,5-alpha-H-tropane-2-beta-carboxylate benzoate (ester) (1R,2R,3S,5S)-2-Methoxycarbonyltropan-3-yl benzoate Blow [Street Name] Girl Lady Rock Toot Cecil Flake Sleighride Badrock Bazooka Bernice Blizzard Cabello Charlie Cocktail Goofball Moonrocks Blast Candy Caviar Freeze Heaven Snort Trails Coca Cola Hell Toke Yeyo Bouncing Powder Chicken Scratch Happy powder EINECS 200-032-7 Florida Snow Sweet Stuff Gold dust [Street Name] Prime Time C Carrie Happy dust [Street Name] 8-Azabicyclo(3.2.1)octane-2-carboxylic acid, 3-(benzoyloxy)-8-methyl-, methyl ester, (1R-(exo,exo))- Foo Foo Kibbles n' Bits Snow (birds) G-Rock [1R-(exo,exo)]-3-(benzoyloxy)-8-methyl-8-azabicyclo[3.2.1]octane-2-carboxylic acid, methyl ester methyl (1R,2R,3S,5S)-8-methyl-3-[(phenylcarbonyl)oxy]-8-azabicyclo[3.2.1]octane-2-carboxylate Cholly [Street Name] Cocaine [USP:BAN] Star dust [Street Name] Green gold [Street Name] DEA No. 9041 Happy trails [Street Name] Line Cocaine (-) 1i7z Epitope ID:158626 SCHEMBL21930 CHEMBL370805 GTPL2286 IDS-NC-004 DTXSID2038443 BDBM22418 (1R,2R,3S,5S)-2-(methoxycarbonyl)tropan-3-yl benzoate 1q72 Cocaine 0.1 mg/ml in Acetonitrile Cocaine 1.0 mg/ml in Acetonitrile ZINC3875336 RX0041 AKOS015965554 DB00907 RX-0041 C01416 Q41576 (1R,5S,8R)-2beta-(Methoxycarbonyl)-3beta-(benzoyloxy)tropane cocaine hydrochloride;Cocaine hydrochloride;(-)-Cocaine hydrochloride [1R-(exo,exo)]-3-(Benzoyloxy)-8-methyl-8-azabicyclo[3.2.1]octane-2-carboxylic Acid Cocaine solution, 1.0 mg/mL in acetonitrile, ampule of 1 mL, certified reference material methyl (2R,3S)-3-(benzoyloxy)-8-methyl-8-azabicyclo[3.2.1]octane-2-carboxylate (1beta,5beta,8-anti)-3beta-Benzoyloxy-8-methyl-8-azabicyclo[3.2.1]octane-2beta-carboxylic acid methyl ester 1-alpha-H,5-alpha-H-Tropane-2-beta-carboxylic acid, 3-beta-hydroxy-, methyl ester, benzoate (ester) (8CI) 8-Azabicyclo[3.2.1]octane-2-carboxylic acid, 3-(benzoyloxy)-8-methyl-, methyl ester, (1R,2R,3S,5S)-(9CI)

Chemical NER Pipeline



- State-of-the-art: .92 F_1 for entity recognition (BioBERT, Lee et al. 2020)
- Open research topics:
  - Joint models for linking and NER
  - Multi-task learning for relations and entities

A glimpse on disease names

- Results are similar for disease names:
  - Several combined dictionaries on manually annotated paper abstracts: .19 Precision, .76 Recall
  - Joint recognition and normalization works pretty well though (.8 F_1)
- Disease name recognition is challenging when compared between social media and scientific text
  - Frequent names are similarly used, infrequent ones are dissimilar
  - Main reason: Ambiguous synonyms in dictionary entry
  - Research direction: learn to align expert and layperson language

Table 3: 7 most similar MeSH concepts.

MeSH ID	Similarity	Canonical name
D006526	0.496	Hepatitis C
D005910	0.463	Glioma
D003920	0.459	Diabetes Mellitus
D006521	0.453	Chronic Hepatitis
D000860	0.451	Hypoxia
D003327	0.446	Coronary Disease
D015658	0.445	HIV Infections
...	...	...

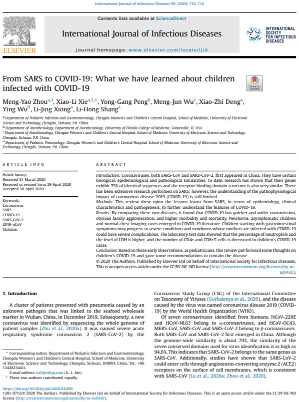
Table 4: 6 least similar MeSH concepts.

MeSH ID	Similarity	Canonical name
...	...	...
D015458	0.170	T Cell Leukemia
D002547	0.155	Cerebral Palsy
C536528	0.122	Van der Woude syndrome
C535984	0.116	Congenital bilateral aplasia of vas deferens
D029461	0.109	Sialic Acid Storage Disease
C537666	0.109	BMD

Summary

- Biomedical information extraction is commonly formulated as
  1. machine-learning based NER
  2. dictionary-based Named Entity Normalization
  3. (relation extraction)
- Biomedical domain is characterized by rich and high-quality resources (mostly)
- Many shared tasks exist for many different entity types:
  - CHEMDNER (Biocreative)
  - BioNLP Infectious Diseases (BioNLP-ST)
  - Drug Adverse Reactions (AMIA 2017)
  - ...
- Many entities: 94M in Pubchem (2017)
- Number of realizations of each entity limited: The challenge is to categorize huge amounts of "classes" to text, though each classification problem is comparably straight-forward. ⇒ Reason for formulation of NER+NEN.

Differences between Scientific Papers and Social Media



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INTERNATIONAL SOCIETY FOR INFECTIOUS DISEASES

From SARS to COVID-19: What we have learned about children infected with COVID-19

Meng-Yao Zhou[a,1], Xiao-Li Xie[a,1,*], Yong-Gang Peng[b], Meng-Jun Wu[c], Xiao-Zhi Deng[a], Ying Wu[d], Li-Jing Xiong[a], Li-Hong Shang[a]

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[b] Department of Anesthesiology, Department of Anesthesiology, University of Florida College of Medicine, Gainesville, Fl, USA
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2019-nCoV
Children

ABSTRACT

Introduction: Coronaviruses, both SARS-CoV and SARS-CoV-2, first appeared in China. They have certain biological, epidemiological and pathological similarities. To date, research has shown that their genes exhibit 79% of identical sequences and the receptor-binding domain structure is also very similar. There has been extensive research performed on SARS; however, the understanding of the pathophysiological impact of coronavirus disease 2019 (COVID-19) is still limited.
Methods: This review drew upon the lessons learnt from SARS, in terms of epidemiology, clinical characteristics and pathogenesis, to further understand the features of COVID-19.
Results: By comparing these two diseases, it found that COVID-19 has quicker and wider transmission, obvious family agglomeration, and higher morbidity and mortality. Newborns, asymptomatic children and normal chest imaging cases emerged in COVID-19 literature. Children starting with gastrointestinal symptoms may progress to severe conditions and newborns whose mothers are infected with COVID-19 could have severe complications. The laboratory test data showed that the percentage of neutrophils and the level of LDH is higher, and the number of CD4+ and CD8+T-cells is decreased in children's COVID-19 cases.
Conclusion: Based on these early observations, as pediatricians, this review put forward some thoughts on children's COVID-19 and gave some recommendations to contain the disease.
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1. Introduction

A cluster of patients presented with pneumonia caused by an unknown pathogen that was linked to the seafood wholesale market in Wuhan, China, in December 2019. Subsequently, a new coronavirus was identified by sequencing the whole genome of patient samples (Zhu et al., 2020a). It was named severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) by the Coronavirus Study Group (CSG) of the International Committee on Taxonomy of Viruses (Gorbalenya et al., 2020), and the disease caused by the virus was named coronavirus disease 2019 (COVID-19) by the World Health Organization (WHO).

Of seven coronaviruses identified from humans, HCoV-229E and HCoV-NL63 belong to α-coronaviruses, and HCoV-OC43, MERS-CoV, SARS-CoV and SARS-CoV-2 belong to β-coronaviruses. Both SARS-CoV and SARS-CoV-2 first emerged in China. Although the genome-wide similarity is about 79%, the similarity of the seven conserved domains used for virus identification is as high as 94.6%. This indicates that SARS-CoV-2 belongs to the same genus as SARS-CoV. Additionally, studies have shown that SARS-CoV-2 could enter cells through angiotensin-converting enzyme 2 (ACE2) receptors on the surface of cell membranes, which is consistent with SARS-CoV (Lu et al., 2020a; Zhou et al., 2020).

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$\Leftarrow$

- Trustworthy
- Fact-oriented, precise language
- Slow publication process

- Unreliable
- Emotional language
- Fast publication

$\Rightarrow$

Differences between Scientific Papers and Social Media


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⇐

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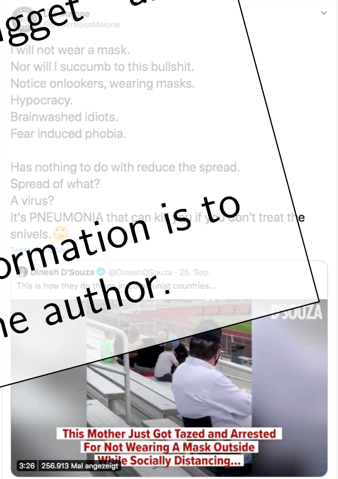
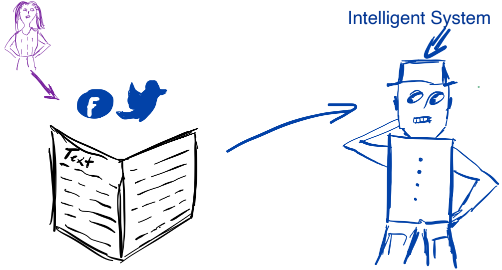


Scientific text:
important information nugget are
facts, entities, relations.

Social media:
an important piece of information is to
gain knowledge about the author.

Outline

Overview



What can we learn about the author of a message?

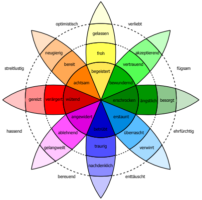
- Personality traits
- Categories (gender, race, nationality, age)
- Expressed emotion, stance, sentiment

Definition of emotions and their linguistic realizations

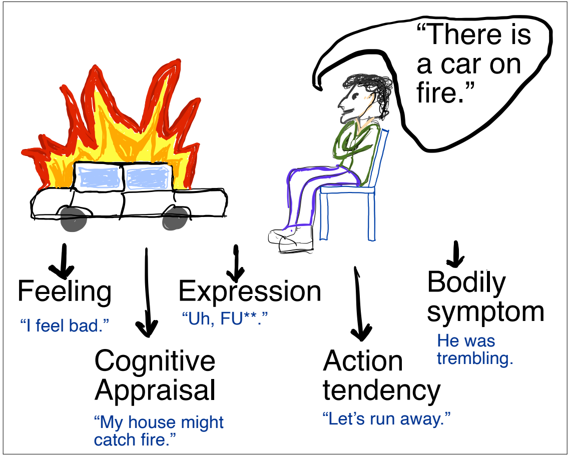
Emotion (Scherer, 2005)

Emotions are "an episode of interrelated, synchronized changes in the states of [...] five organismic subsystems in response to the evaluation of a [...] stimulus-event ..."

Ekman (1999)



Plutchik (2001)



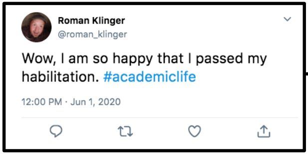
Dictionaries?

- A list of emotion synonyms? No.
- Dictionaries exist!
- Popular Example: NRC Dictionary
- This is a rich resource, performance depends on application and domain.

Examples

- **Anger:**
  aggression, devil, neglected, obstacle
- **Joy:**
  aesthetics, achieve, cathedral, laughter
- **Sadness:**
  unfair, scarce, napkin, tough

Starting point and Motivation



Emotion Analysis Systems

Category: Joy
Intensity: 0.8
Valence: 0.9
Arousal: 0.7

Feeler: “I”
Cue: “so happy”
Cause: “passed my habilitation”

Semantic Role Labeling

- Provide more information to downstream applications
- Challenging sequence labeling task

Who Feels What and Why?
Annotation of a Literature Corpus with Semantic Roles of Emotions

Evgeny Kim and **Roman Klinger**
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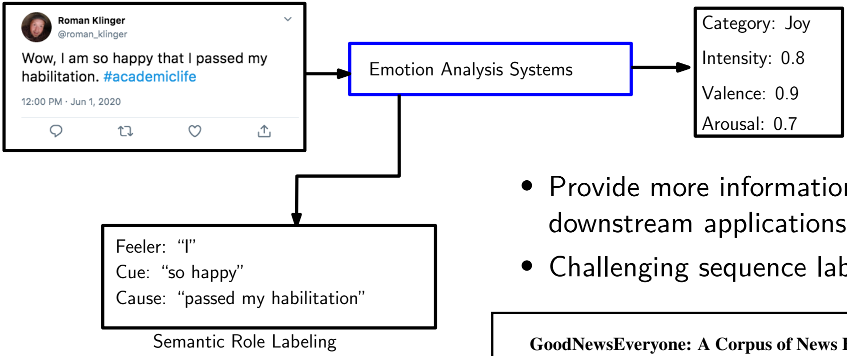
Starting point and Motivation



- Provide more information to downstream applications
- Challenging sequence labeling task

GoodNewsEveryone: A Corpus of News Headlines Annotated with Emotions, Semantic Roles, and Reader Perception

Laura Bostan, Evgeny Kim, Roman Klinger
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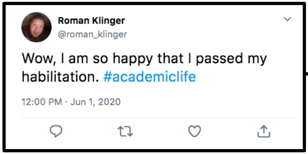
Starting point and Motivation



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Token Sequence Labeling vs. Clause Classification for English Emotion Stimulus Detection

Laura Oberländer and **Roman Klinger**
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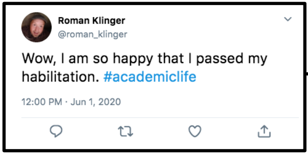
Pfaffenwaldring 5b, 70569 Stuttgart, Germany
{laura.oberlaender,roman.klinger}@ims.uni-stuttgart.de

Starting point and Motivation



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Semantic Role Labeling

- Provide more information to downstream applications
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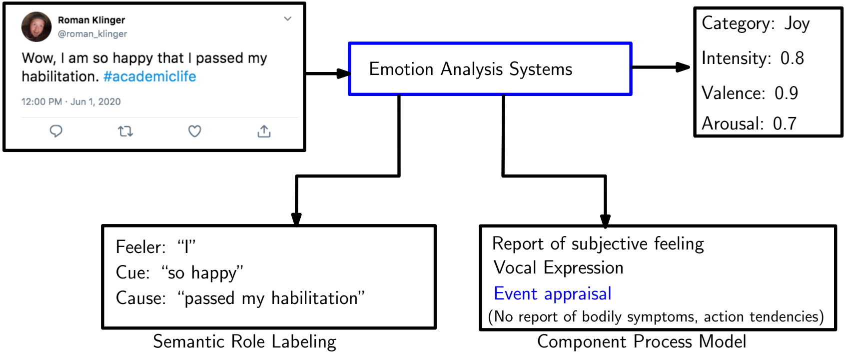
Experiencers, Stimuli, or Targets:
Which Semantic Roles Enable Machine Learning to Infer the Emotions?

Laura Oberländer, Kevin Reich, and **Roman Klinger**
Institut für Maschinelle Sprachverarbeitung, University of Stuttgart, Germany
`{firstname.lastname}@ims.uni-stuttgart.de`

Starting point and Motivation



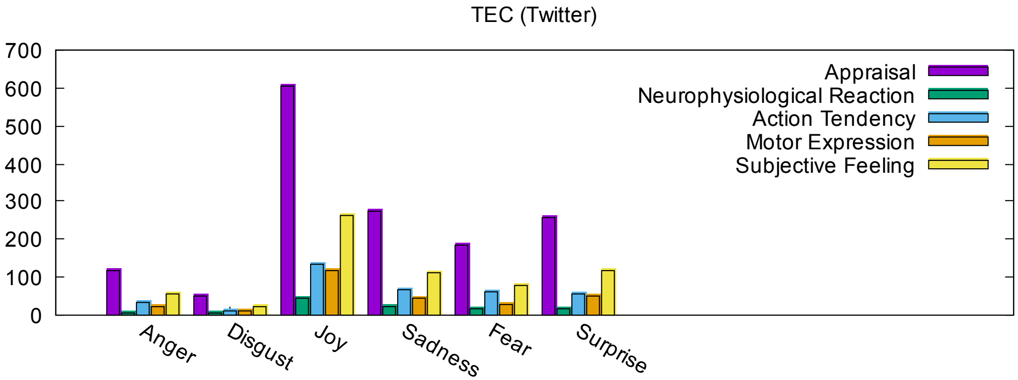
- Additional information for downstream applications
- Supports emotion detection

Intermediate Results on Emotion Component Model

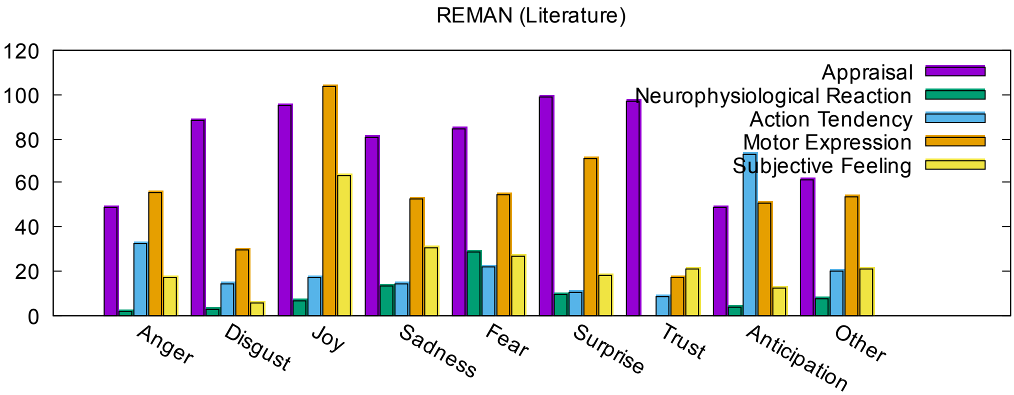
- Is this really the case?
- All components play a role in each emotion?
- How can recognizing the components contribute to emotion recognition then?

⇒ Annotation study on literature and Twitter
(part of the recent theses by Amelie Heindl and Felix Casel)

Intermediate Results on Emotion Component Model

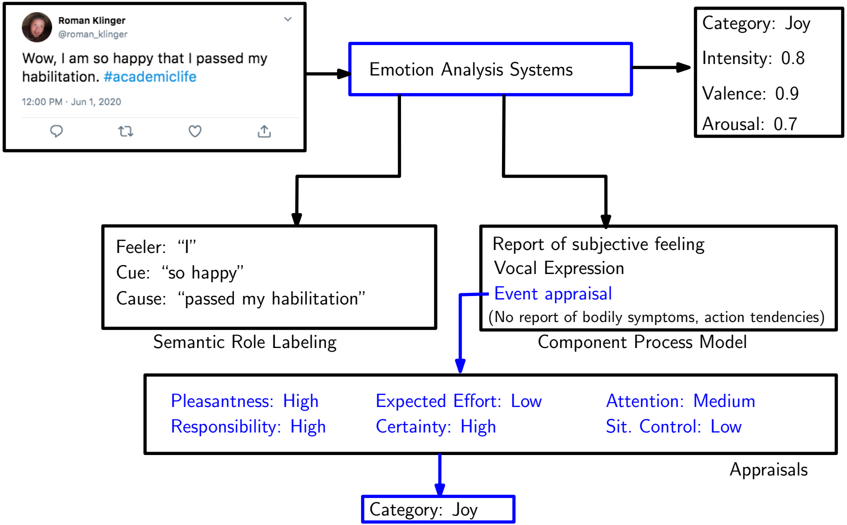


Intermediate Results on Emotion Component Model

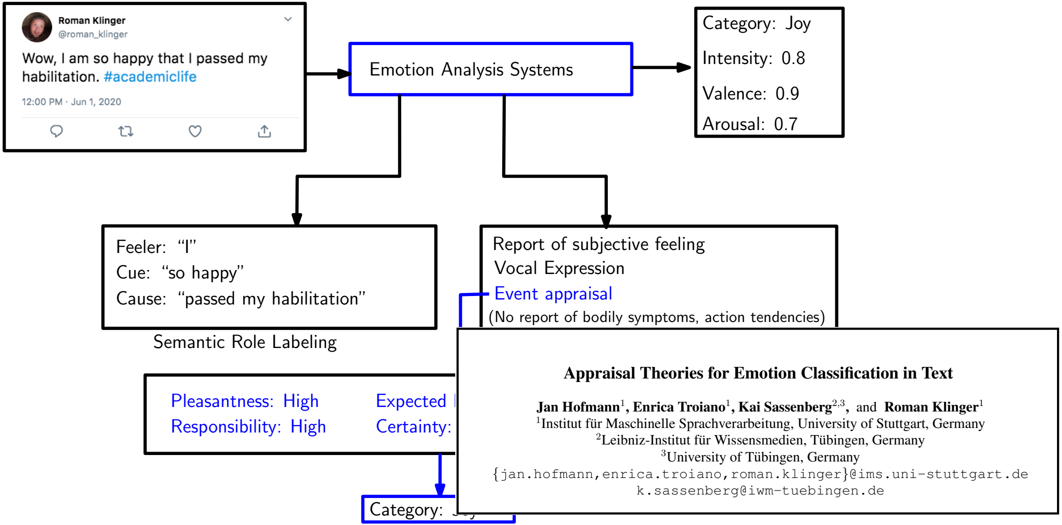


- Providing component information to emotion classifier helps in literature
- Multi-task learning of components and emotions shows improvements for both corpora

Starting point and Motivation



Starting point and Motivation

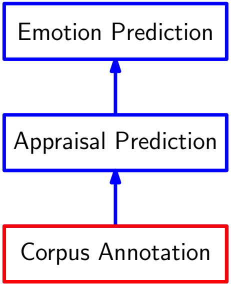


Appraisal Annotation

Most probably, at the time when the event happened, the writer...

- ...wanted to devote further attention to the event. (Attention)
- ...was certain about what was happening. (Certainty)
- ...had to expend mental or physical effort to deal with the situation. (Effort)
- ...found that the event was pleasant. (Pleasantness)
- ...was responsible for the situation. (Responsibility)
- ...found that he/she was in control of the situation. (Control)
- ...found that the event could not have been changed/influenced by anyone. (Circumstance)

Corpus Selection



- Which corpus to use to study appraisals in text?
  - "Remember an event which triggered [emotion] and describe it: 'I felt [emotion word], when…' "
  - 1001 event descriptions, stratified by emotion (anger, disgust, fear, guilt, joy, shame, sadness)

Crowdsourcing and Validating
Event-focused Emotion Corpora for German and English

Enrica Troiano, Sebastian Padó and **Roman Klinger**
Institut für Maschinelle Sprachverarbeitung
University of Stuttgart, Germany
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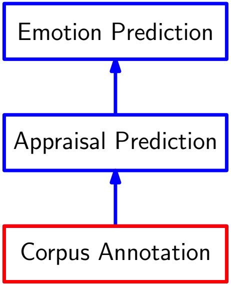
Corpus Selection



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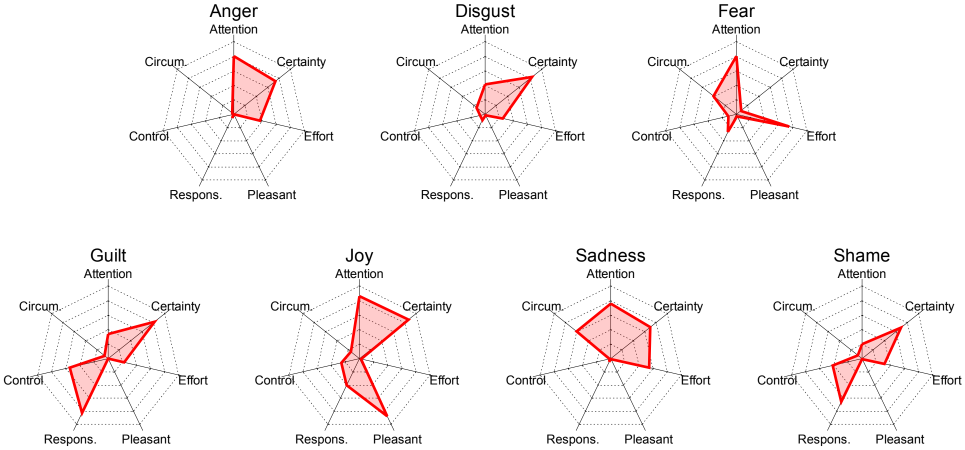
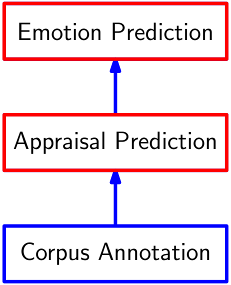
Examples

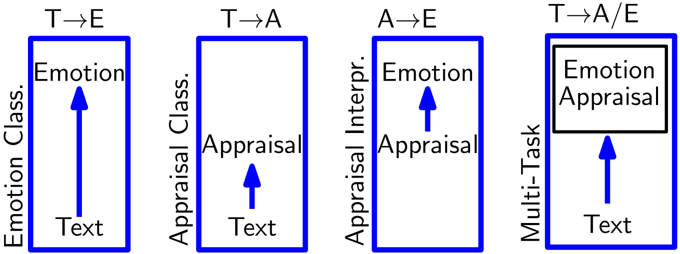
- I felt [sadness] when I saw a homeless cat on the street.
- I felt [shame] when someone commented that I was looking very untidy.
- I felt [anger] when the police did not update me on a crime.

Annotation Results



Modelling and Experimental Setting

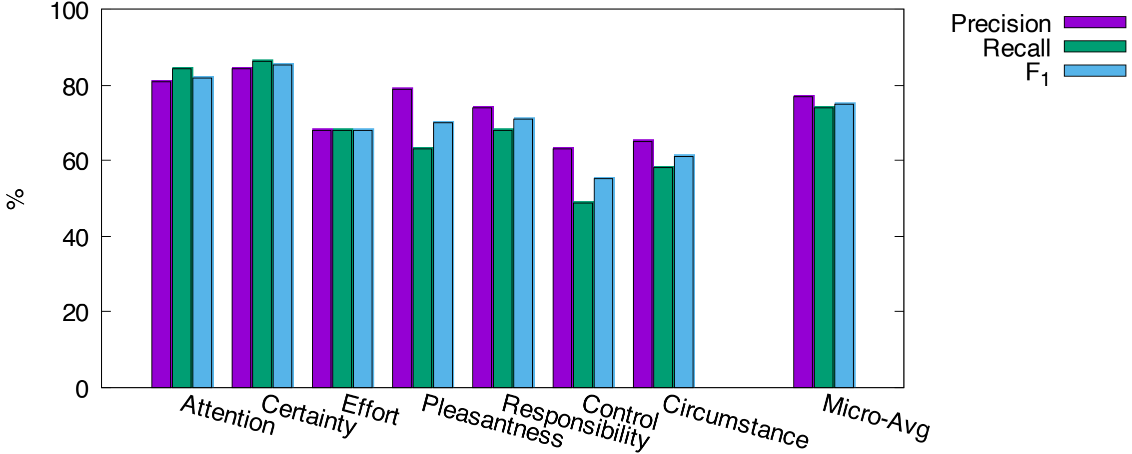




- Text classifiers: Convolutional neural network, pretrained GloVe 300-dimensional embeddings, filter sizes 2,3,4, ReLu activation, dropout 0.5
- Emotion from Appraisal:
  Fully connected neural network with two layers
- Evaluation via 10×10-fold CV

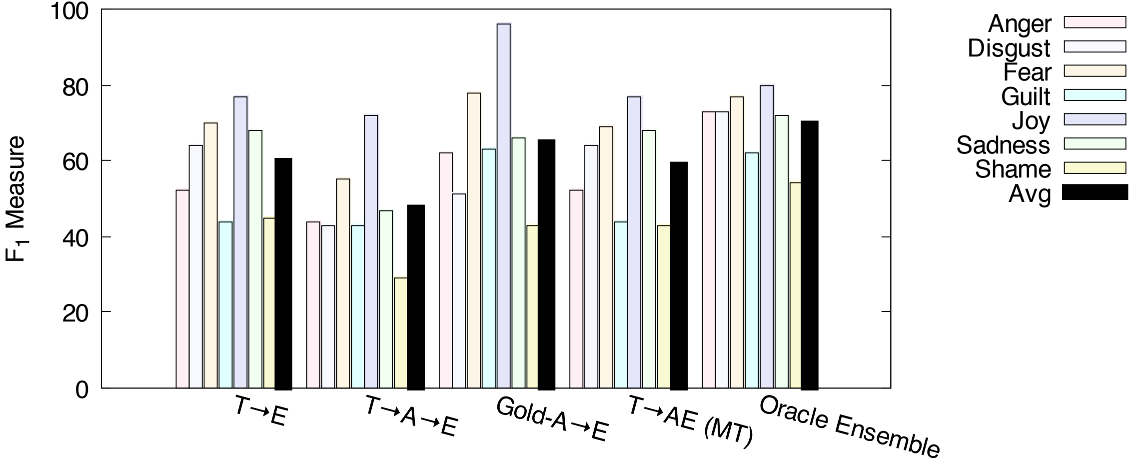
Modelling Results

How well can we predict appraisal dimensions from text?



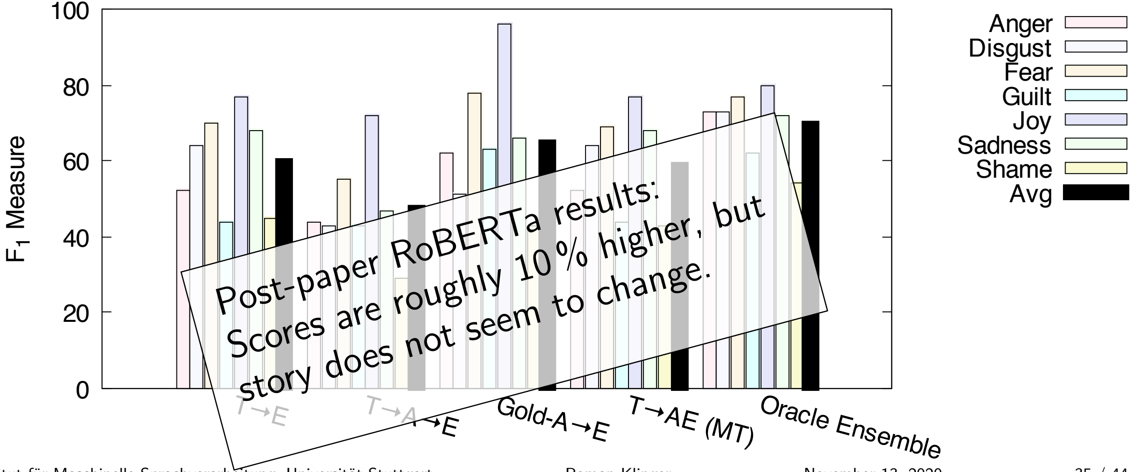
Modelling Results

Can this approach improve emotion classification?



Modelling Results

Can this approach improve emotion classification?



Examples

Gold	A→E	T→E	Text
Anger	Anger	Disgust	when I saw someone mistreating an animal.
Disgust	Disgust	Shame	because I ate a sausage that was horrible.
Disgust	Disgust	Fear	when I was on a ferry in a storm and lots of people were vomiting.
Guilt	Guilt	Shame	when I took something without paying.
Guilt	Guilt	Joy	for denying to offer my kids what they demanded of me.
Joy	Joy	Disgust	when I found a twenty pound note on the ground outside.

Summary

- Emotion classification directly from text remains the best approach (so far)
- Appraisal prediction has potential to improve emotion classification
- Oracle approach shows that the two methods are complementary

- Few concepts: possible to tackle as standard text classification approach (optionally enriched and modelled jointly with text segments)

Next (concrete) Steps in Emotion Analysis

Appraisal:

- Large scale crowdsourcing of events with appraisal labels from experiencer
- Annotation of structured event representations with appraisals
- End-to-end joint pipeline learning of appraisal and emotions
- Explore other model architectures
- DFG Project CEAT starts in January 2021 (with Laura Oberländer as postdoc)

Role labeling:

- Multimodality: Emotion stimuli in images (DFG project in preparation with C. Silberer)
- Joint modelling of roles (final WP in DFG Project SEAT)

Outline

Biomedical entities and emotions

Biomedical information extraction

- Many entities
- Comparably few linguistic realizations
- Huge established databases available
- Precision for finding and linking entities is a challenge

Emotion analysis

- Few concepts to link
- Many linguistic realizations
- Conceptualization under constant discussion
- Precision and recall are both challenging

Why do I care about both?

- Emotions as a fact:
  Which events influence public health, well-being, and quality of life of individuums and peoples?
- Emotions as factor:
  Is misinformation/desinformation correlated to particular expressed emotions?

- New DFG Project starting 2021 on biomedical fact checking (with Amelie Wührl as PhD student)

Vision and Mission

- Make accessible and understand
  - communication of relational (biomedical) information across different sources, scientific text, social media, experts and laypeople
  - realizations of psychological concepts like emotions across different domains, modalities and realization patterns
- Link medical information and psychological concepts as they occur “in the wild”.
  - Downstream tasks: fact-checking, misinformation detection, pharmacovigilance, opinion mining, ...
- Develop resources and machine learning methods to enable these goals.

Ethical Considerations

- Systems suffer from biases
- Systems are not reliable
- Corpora and systems do not represent all groups in a population equally
- Concepts are analyzed which people might not even be aware of
- Analyses should never enable any inference about individuals,
  results should only be reported in aggregated form.

Thank you for your attention.
Questions? Remarks?

?

(please type a Q in the chat if you have a question)

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Institut für
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Computational Natural Language Understanding: Use cases in the life sciences and psychology

Inaugural Lecture

November 13, 2020

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