More Than a Feeling: Emotion in Text

Candidacy Examination

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Introduction
Introduction

Incorporating Psychological Models

• Scientists make modeling assumptions to study real-world phenomena
• Natural language processing - author and audience
• Humans produce and consume the text we study (so far), and our models lack crucial information if we do not recognize this
• A domain-specific understanding of these phenomena can help incorporate them
Focus for this talk: emotion in text

1. Introduction
2. Emotion and Influence
3. Emotion Classification
4. Uniting NLP Methods with Psychological Theories
5. Conclusion
Emotion and Influence
• Studying emotion and influence is not a new idea
In Argumentation Theory

- Studying emotion and influence is **not** a new idea
- Western roots in Aristotle (**Alan Brinton**)
  - Recognition by some of the earliest, most influential Western scholars
  - Pathos - one of Aristotle’s essential means of persuasion
  - Pathos related to morality and virtue for Aristotle
  - Persuading to feel emotion vs. emotion as basis for action
In Argumentation Theory

- Western roots in Aristotle (Alan Brinton)
- Argumentation and logic (Michael Gilbert)
  - Proposition: emotional and factual argument are *equally* fuzzy and ambiguous
  - Treats emotion under the *acceptability, relevance, sufficiency framework*
Western roots in Aristotle (Alan Brinton)
Argumentation and logic (Michael Gilbert)
- Proposition: emotional and factual argument are equally fuzzy and ambiguous
- Treats emotion under the acceptability, relevance, sufficiency framework
- In order to study the real world, we must study the things that actually happen, not just their idealized models
Emotion and influence highly studied in psychology
• Emotion and influence highly studied in psychology

• Processing arguments (Schwarz et al.)
  • Critical review of candidate mechanisms for how emotion affects persuasion
  • Central vs. peripheral processing
• Processing arguments (Schwarz et al.)
  • Mood as peripheral cue hypothesis
  • Mood congruency hypothesis
  • Change in criteria hypothesis
  • Motivational hypothesis
  • Cognitive capacity hypothesis
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In Psychology

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- Critical review of candidate mechanisms for how emotion affects persuasion
- Conclusion: negative mood more conducive to central processing
• Processing arguments (Schwarz et al.)
• Making arguments (Villata et al.)
  • Used facial expression to examine emotions felt while arguing
  • Some significant correlations observed (e.g., sadness $\propto$ withdrawal)
In Psychology

- Processing arguments (Schwarz et al.)
- Making arguments (Villata et al.)
  - Used facial expression to examine emotions felt while arguing
  - Some significant correlations observed (e.g., sadness \(\propto\) withdrawal)
  - Emotion and the process of making an argument do interact
In Computer Science

- Effects of argument type by audience (*Lukin et al.*)
  - Interaction of argument type and audience personality
  - No measures of long-lasting belief change, but definite short-term effects

- Characterizing emotional vs. logical arguments (*Oraby et al.*)
  - Syntactic patterns extracted from emotional and logical arguments
  - Logical arguments more structural, emotional more vivid and immediate
In Computer Science

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  - Syntactic patterns extracted from emotional and logical arguments
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- ...and...?
Emotion and Influence

Summary

- Emotion plays a significant role in influence and has been studied extensively in multiple fields
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• Emotion interacts with cognition—in the author and audience
Emotion and Influence

Summary

- Emotion plays a significant role in influence and has been studied extensively in multiple fields
- Emotion interacts with cognition—in the author and audience
- However, there is a dearth of computational work in this area
Emotion Classification
Emotion Classification

- Problem: given a piece of text, assign it one (or more) emotion label(s)

  Smiling like the cat who got the canary right now. Just got this beauty from Publix....#MyDayIsMade❤️🔥😍😊😂рап  

- Typically a supervised machine learning problem with discrete emotion labels
- Greatly accelerated with popularization of social media data

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1https://twitter.com/YLKATDelta/status/1117913821513838597
A Very Abridged History of Emotion Classification

- Learning Emotions (2008)
- Image Descriptions (2012)
- Emotions from Text (2005)
- EMOTEX (2014)
- EmoNet (2017)
- DeepMoji (2017)
- DeepEmo (2018)
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- NTUA-SLP (2018)
- Twitter Big Data (2012)
- Multi-Task (2018)
Emotion Categories

Ekman’s Six Basic Emotions (universal facial expressions)

Plutchik’s Wheel of Emotions (evolutionarily adaptive behaviors)

Other Models
- Circumplex model
- Geneva emotion wheel
- Valence/sentiment
- Still many more in psychology literature
- etc.....
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A Very Abridged History of Emotion Classification

Other Emotion Schemes

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A Very Abridged History of Emotion Classification

Traditional ML

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Non-Neural Approaches

- Linear classifiers (SVM, Naïve Bayes)
- Decision and distance algorithms (decision trees, k-nearest neighbor, latent semantic analysis)
Feature Representation

- Bag-of-ngram features
- Lexical features (punctuation, emoticons, ALL CAPS)
- Semantic features (POS tags, negations)
- Curated lexicons (LIWC, WordNet, DAL, MPQA Subjectivity Lexicon)
A Very Abridged History of Emotion Classification

Deep Learning

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Deep Learning (Supervised)

Recurrent Networks

- Long Short-Term Memory Networks (NTUA-SLP, DeepMoji)
- Gated Recurrent Neural Networks (EmoNet, Multi-Task)
- “Tricks”: bidirectional, attention

Convolutional Networks

- A sort of neural n-gram approach (DeepEmo, Emo2Vec)
Emotional Embeddings

- Model-specific word embedding layers
- **NTUA-SLP** - add 10 affective dimensions and spread scores from hand-annotated words
- **DeepEmo** - collect syntactic patterns indicative of different emotions
A Very Abridged History of Emotion Classification

Hand-Annotated Corpora

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Hand-Annotated Corpora

- A small number of manual annotators ([Emotions from Text, Learning Emotions](#))
- Crowdsourced annotations ([Image Descriptions, Multi-Task](#))
A Very Abridged History of Emotion Classification

Distant Labeling

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Distant Labeling - Social Media

- **Twitter hashtags** - EmoNet, EMOTEX, DeepEmo, Twitter Big Data, Emo2Vec, Multi-Task
- **DeepMoji** - Tweets with emojis
- **Image Descriptions** - LiveJournal posts (author provides a mood)

**Validation studies** - Crowd annotations match distant labels fairly well and inform preprocessing (e.g., hashtags at end of Tweet only)
A Very Abridged History of Emotion Classification

Multi-Task Learning

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Multi-task Learning

- **Multi-Task** - same task, two different datasets (distantly labeled vs. hand-annotated)
- **Emo2Vec** - seven tasks (emotion classification/intensity, sentiment, sarcasm, stress, abusive language, personality, insults)
A Very Abridged History of Emotion Classification

Transfer Learning

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Transfer Learning

- **NTUA-SLP** - pretraining on much larger sentiment dataset (SemEval 2017); fine-tuned whole model simultaneously

- **DeepMoji** - pretraining on emoji prediction task; fine-tuned using chain-thaw approach
A Very Abridged History of Emotion Classification

F1 Comparison

- Learning Emotions (2008) - 0.18
- Image Descriptions (2012) - 0.52
- Twitter Big Data (2012) - 0.65
- EMOTEX (2014) - 0.83
- EmoNet (2017) - 0.90
- DeepMoji (2017) - 0.56
- DeepEmo (2018) - 0.72
- Emo2Vec (2018) - 0.47
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- Multi-Task (2018) - 0.65

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A Very Abridged History of Emotion Classification

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- Computational research in affectual text processing is expanding
  - Distant labeling and deep learning have had a huge impact
  - Adjacent problems: emotion intensity, causes of emotion, etc.
Computer research in affectual text processing is expanding

- **Distant labeling and deep learning** have had a huge impact
- Adjacent problems: emotion intensity, causes of emotion, etc.
• Computational research in affectual text processing is expanding
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• Little work done to validate our choice or use of psychological theory
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Uniting NLP Methods with Psychological Theories
NLP Methods and Psychological Theories

- Psychology theory
- Psychology statistics
- NLP methods

Arrows indicate:
- Informed models
- Empirical testing
Useful Theories from Psychology

- Psychology theory can influence how we build models and collect our data
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- **How we talk about and present emotions can change how we and our annotators perceive them**
NLP Methods and Psychological Theories

- Psychology theory
- Psychology statistics
- NLP methods

Flow:
- Informed models from Psychology theory to NLP methods
- Empirical testing from NLP methods to Psychology statistics
- Informed models from Psychology statistics back to Psychology theory

Elsbeth Turcan (Columbia CS) Emotion in Text
Benefits of NLP Methods

- Psychology and health research tends to rely on human experts and shy away from textual data
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- Analyzing motives for self-injury (*Snir et al.*)
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  - Implicit power motive: individual’s tendency to seek influence
  - Examined how this motive was expressed and received
  - Text data was coded and manipulated by hand, so sample size was small
NLP Methods and Psychological Theories

Psychology theory

Psychology statistics

NLP methods

empirical testing

informed models

large-scale analysis

statistical rigor
## Integration: NLP Tasks

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## Integration: Mental Health and Psychology

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- Careful analysis of textual features bolsters their trustworthiness
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Conclusion
Recap

- Humans produce and consume the text we study (so far), and our models lack crucial information if we do not recognize this.
Recap

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- **Emotion has been recognized as a valid component of influence, but is understudied in the computational literature**
Recap

- Humans produce and consume the text we study (so far), and our models lack crucial information if we do not recognize this.
- Emotion has been recognized as a valid component of influence, but is understudied in the computational literature.
- **Affectual text processing is a growing field, but lacking in psychological grounding.**
Recap

- Humans produce and consume the text we study (so far), and our models lack crucial information if we do not recognize this.
- Emotion has been recognized as a valid component of influence, but is understudied in the computational literature.
- Affectual text processing is a growing field, but lacking in psychological grounding.
- **External theory and NLP methods complement one another to draw conclusions supported by domain experts and the power of big data.**
Recap

- Humans produce and consume the text we study (so far), and our models lack crucial information if we do not recognize this.
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- External theory and NLP methods complement one another to draw conclusions supported by domain experts and the power of big data.
- *If we apply it carefully, external theory can help us build more informed and interpretable models that better represent the real world.*
Recap

- Humans produce and consume the text we study (so far), and our models lack crucial information if we do not recognize this.
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**Thank you for listening!**