Modeling Naive Psychology of Characters in Simple Commonsense Stories

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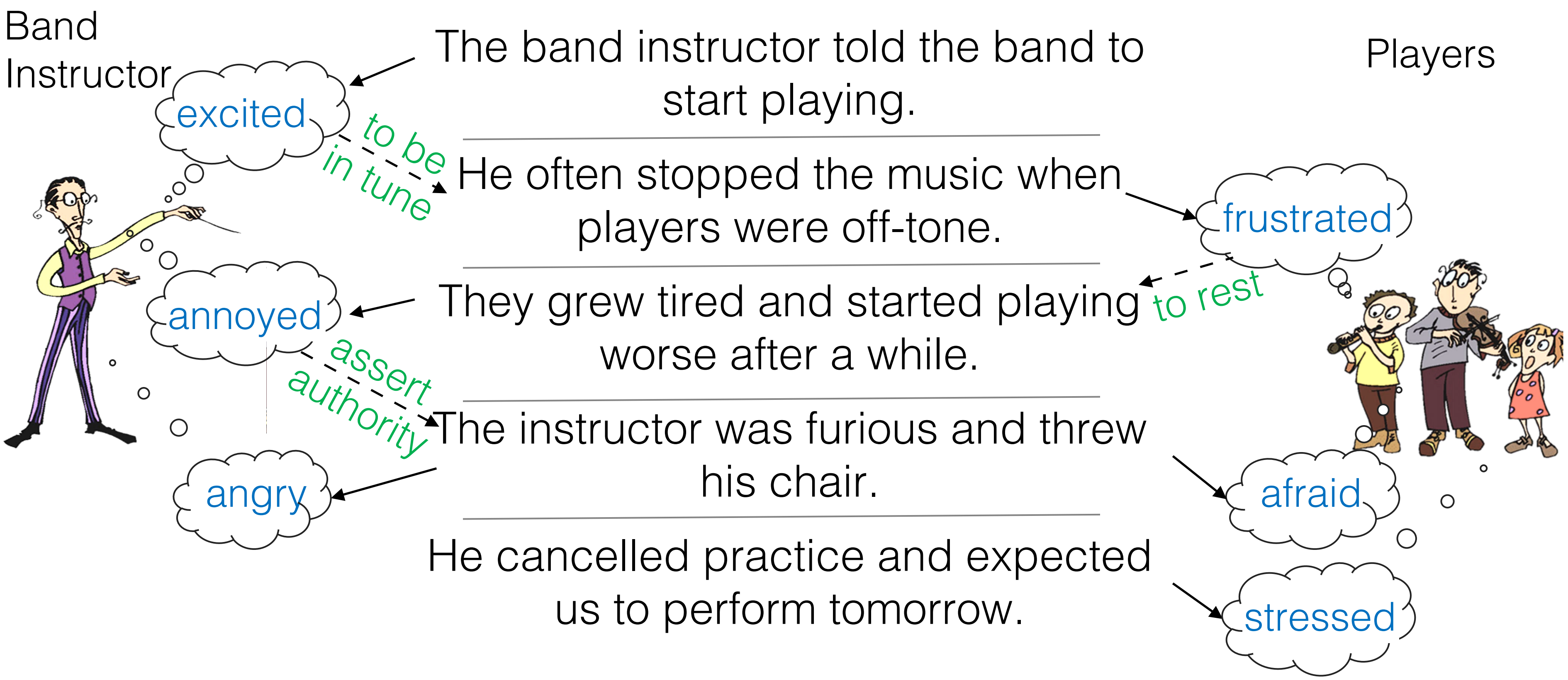
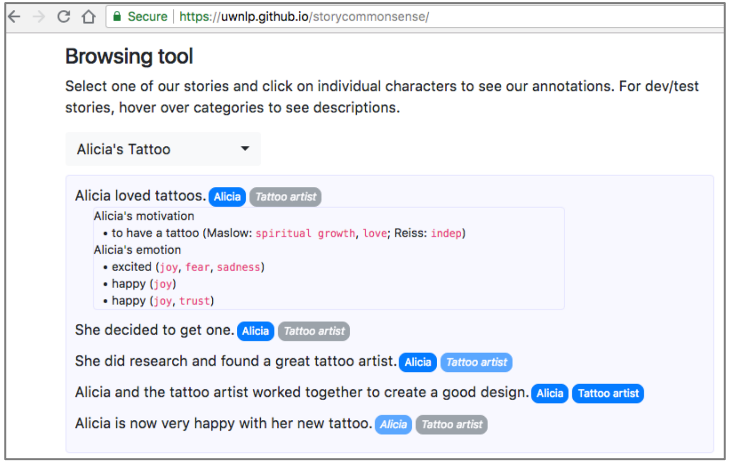
Inferring Character State



Reasoning about Naïve Psychology

New Story Commonsense Dataset:

- Open text + psychology theory
- Complete chains of mental states of characters
- Implied changes to characters
- Contextualized reasoning



https://uwnlp.github.io/storycommonsense/

How do we represent naïve psychology?

The band instructor told the band to start playing.
<u>He often stopped the music when players were off-tone.</u>

Psychology Theories

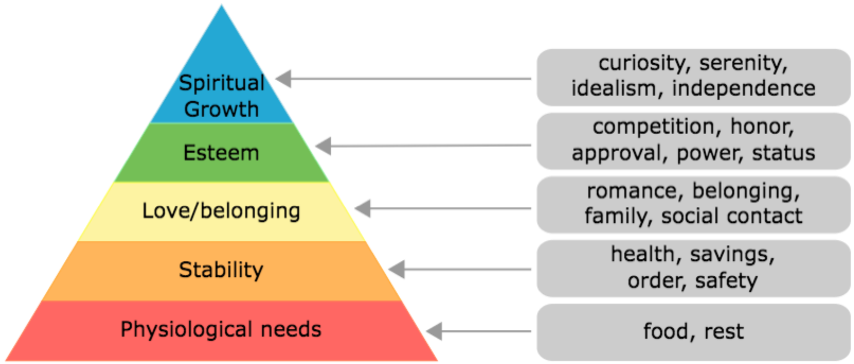
Natural Language

Instructor

Psychology Theories				Natural Language
Esteem	← wants	Instructor	wants →	To create a good harmony
Anger	← feels	Instructor	feels →	frustrated

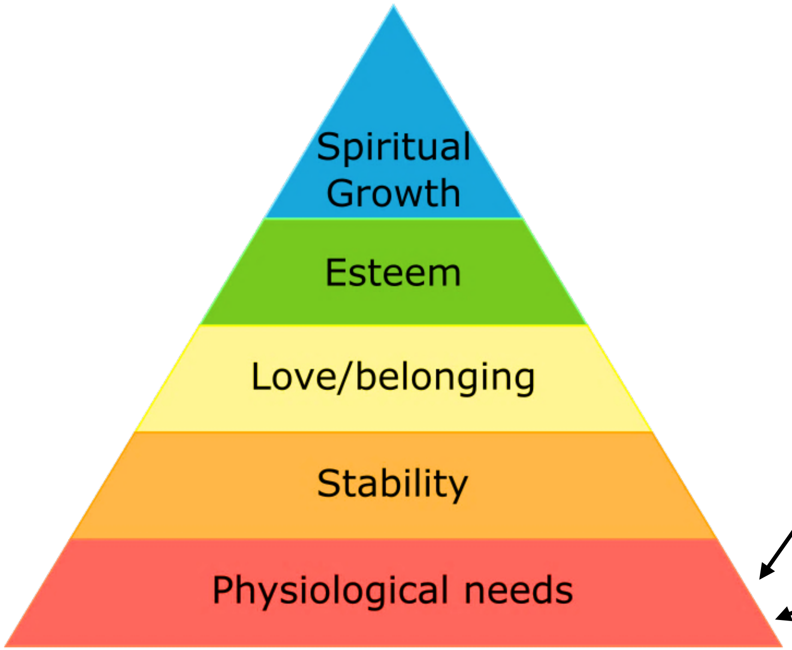
Naïve Psychology Annotations

- *Motivation:*
  - Causal source to actions
  - Motivational theories



- *Emotional Reaction:*
  - Causal effect of actions
  - Theories of emotion

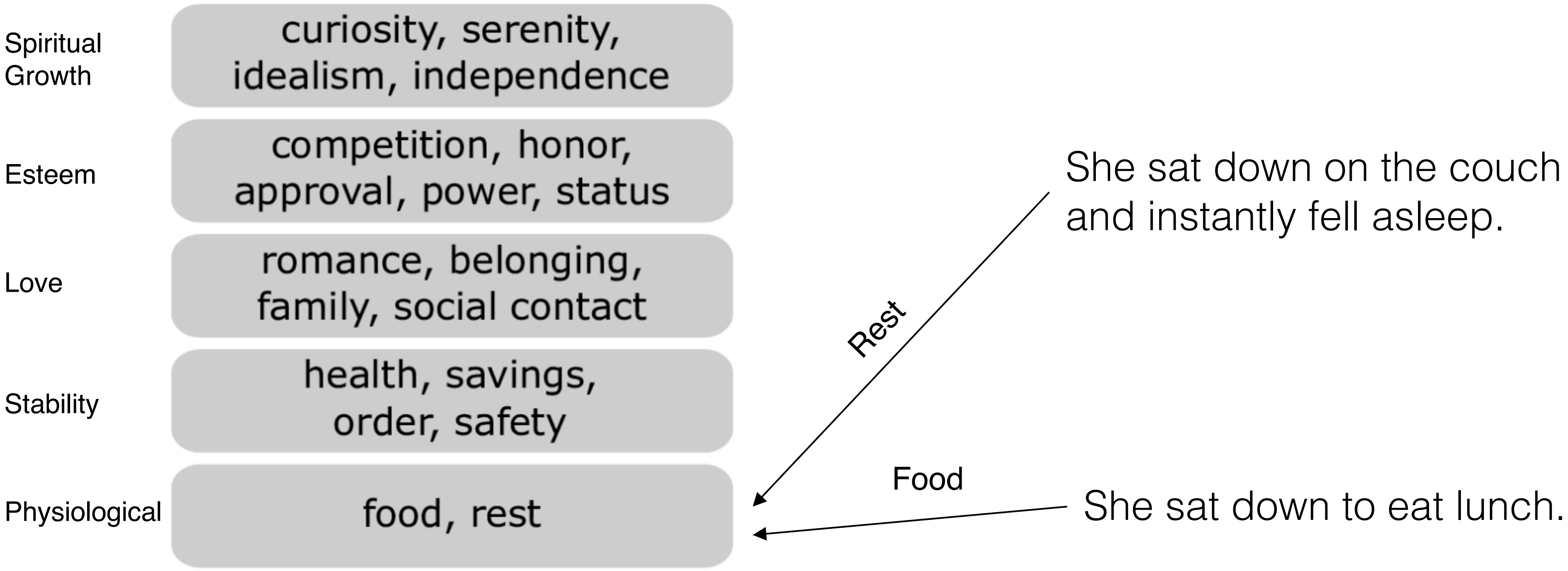
Motivation: Maslow Hierarchy of Needs (1943)



She sat down on the couch and instantly fell asleep.

She sat down to eat lunch.

Motivation: Reiss Categories (2004)



Emotional Reaction: Plutchik (1980)

Plutchik's Wheel

8 "main" emotions:

Their favorite uncle died.

↓

feel Sadness

Suddenly, they heard a loud noise.

↓

feel Fear, Surprise

Implicit Mental State Changes

The band instructor told the band to start playing.
He often stopped the music when players were off-tone.
They grew tired and started playing worse after a while.
<u>The instructor was furious and threw his chair.</u>

How are players affected?

→ implicitly involved

→ inference in these cases

Tracking Mental States

The band instructor told the band to start playing.
He often stopped the music when players were off-tone.
They grew tired and started playing worse after a while.
The instructor was furious and threw his chair.
<u>He cancelled practice and expected us to perform tomorrow.</u>

Why does the instructor cancel practice?

→ based on previous info

→ need to incorporate context

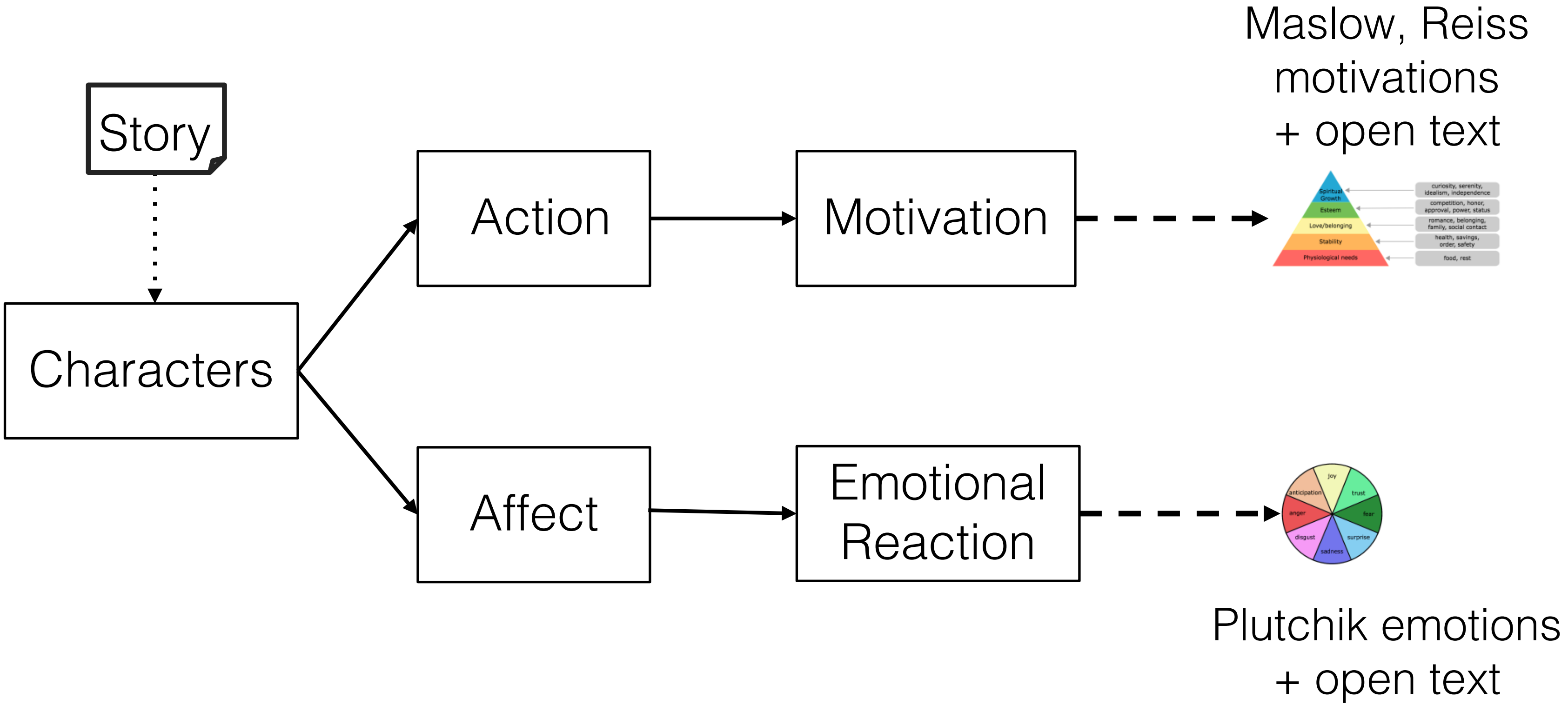
Related Work

- Reasoning about narratives (Mostafazadeh et al 2016)
- Detecting emotional content (Mohammad et al 2013) or stimuli (Gui et al 2017) of a statement

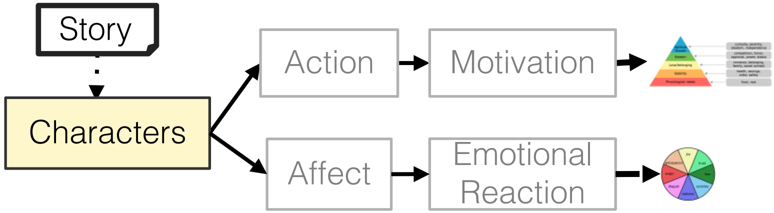
Our work:

- Both motivation and emotion for a character’s outlook
- Leverage psychology theories and natural language explanations

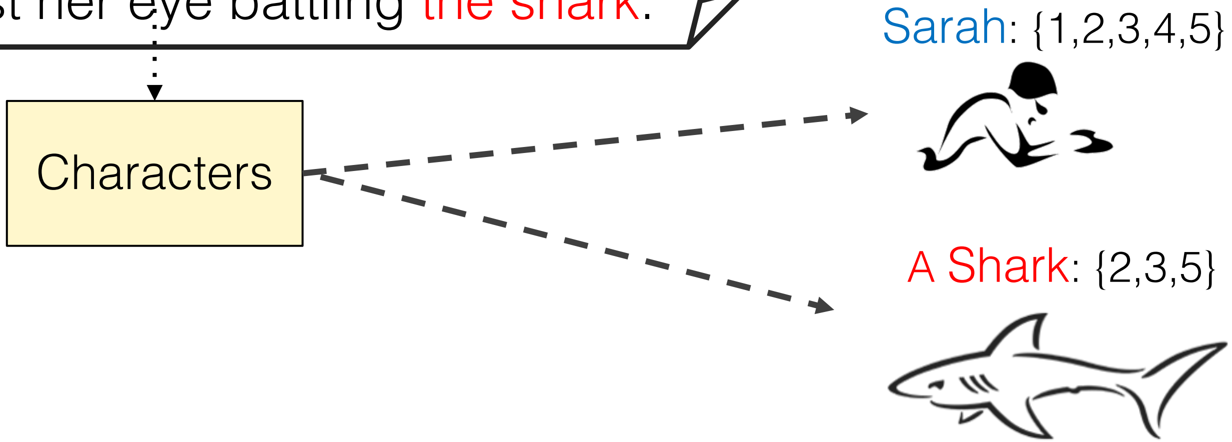
Full Annotation Chain



Full Annotation Chain



Sarah is swimming.
Sarah gets attacked by a shark.
Sarah fights off the shark.
Sarah escapes the attack.
Sarah lost her eye battling the shark.



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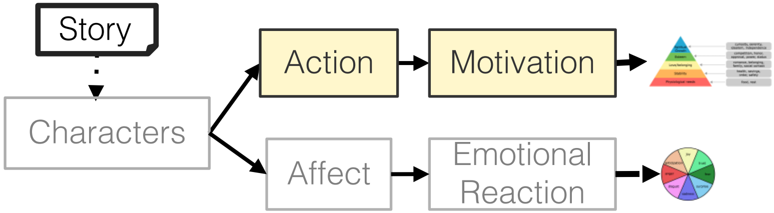

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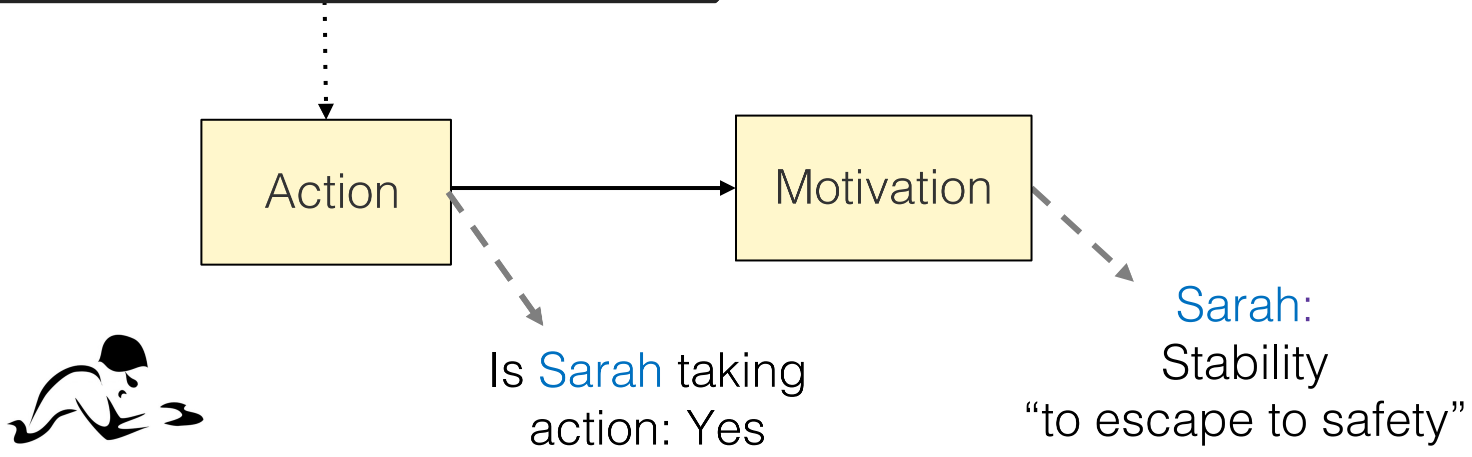
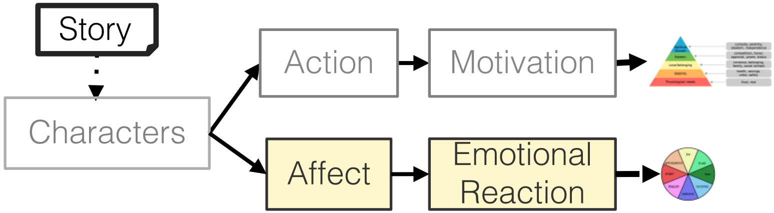




Full Annotation Chain

Sarah is swimming.
Sarah gets attacked by a shark.
Sarah fights off the shark.

Affected

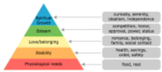
Emotional Reaction

Does the Shark have a reaction?
Yes

Shark:
Anger,
“aggressive”

Data Collection Summary

Over 300k low-level annotations for 15k stories from ROC training set

	Open-text	*Open-text + categories*		
	train	dev	test	
# character-line pairs	200k	25k	23k	
 … w/ motivation change	40k	9k	7k	*>50k motiv. changes*
 … w/ emotional reaction change	77k	15k	14k	*>100k emotion changes*

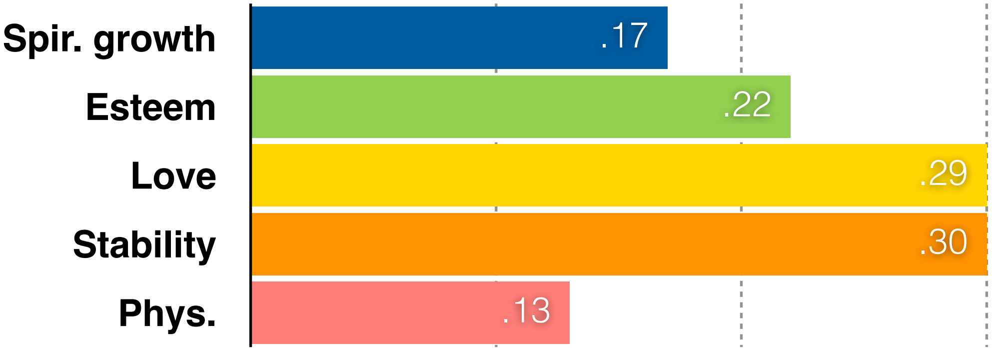
Annotated Data Distributions (Motivation)

- Fair amount of diversity in the open-text
- ~1/3 have positive motivation change:

Sampled Open-text Explanations

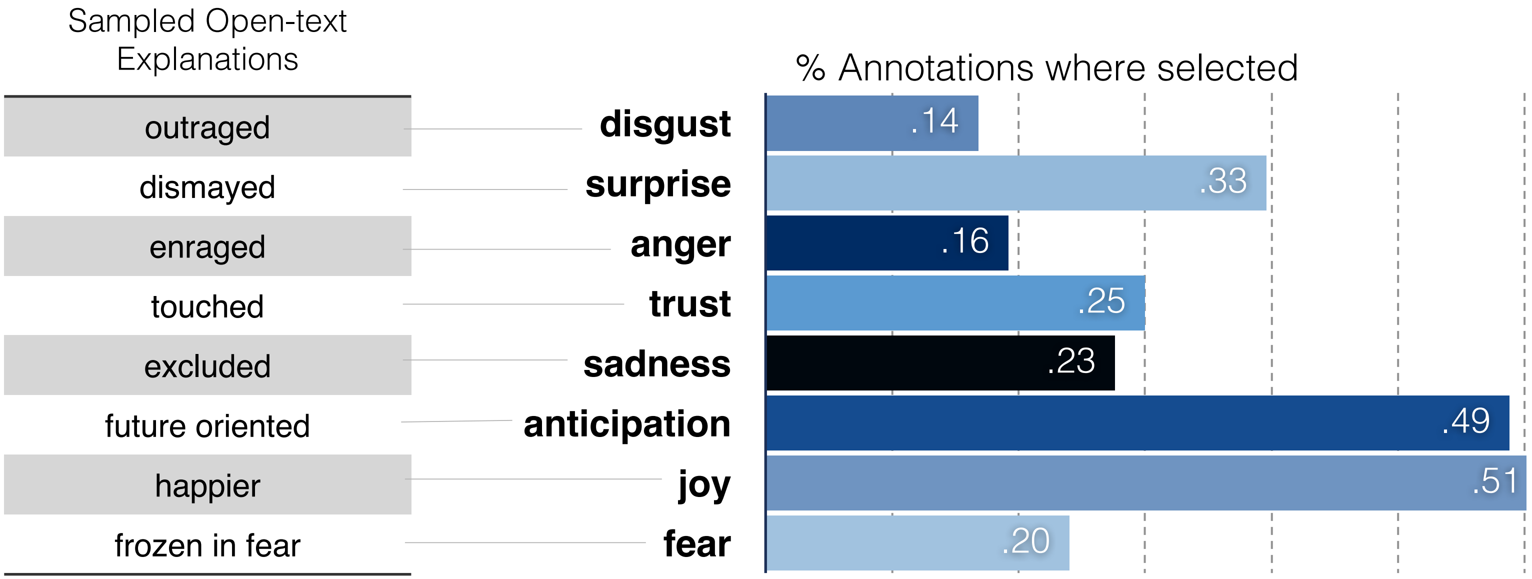
become experienced
meet goal; to look nice
to support his friends
be employed; stay dry
rest more; food

% Annotations where selected



Annotated Data Distributions (Emotion)

- Lots of happy stories
- ~2/3 have positive emotion change:



New Tasks

Given a story excerpt and a character can we explain the mental state:

- Explanation Generation: Generate open-text explanation of motivation/emotional reaction

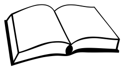
- State Classification: Predict Maslow/Reiss/Plutchik category

Task 1 - Explanation Generation

Explain mental state of character using natural language

Input

The band instructor told the band to start playing.



Story Text Excerpt + Character

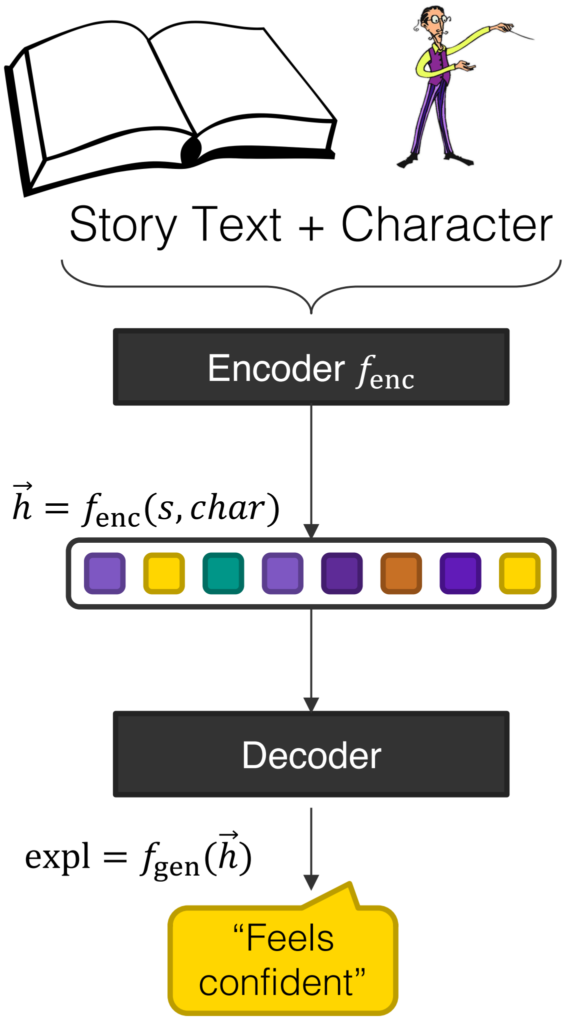
Output

“Feels confident”

Open Text Explanation

Modeling

- Using encoder-decoder framework
- Encoders - LSTM, CNN, REN, NPN
- Decoder for generation: single layer LSTM



Encoding Modules

Given entity e_j and line x^s (and entity-specific context sentences $x^c[e_j]$)

$$\boldsymbol{h} = \boldsymbol{f}_{\mathbf{enc}}\left(\boldsymbol{x}^s, \boldsymbol{x}^c[\boldsymbol{e}_j]\right)$$

Encoding functions:

- CNN, LSTM:
  encode last line and context -- concatenate

Entity Modeling

- Recurrent Entity Networks (Henaff et al 2017)
    - Store separate memory cells for each story character
    - Update after each sentence with sentence-based hidden states

- Neural Process Networks (Bosselut et al 2018)
    - Also has separate representations for each character
    - Updates after each sentence using learned action embeddings

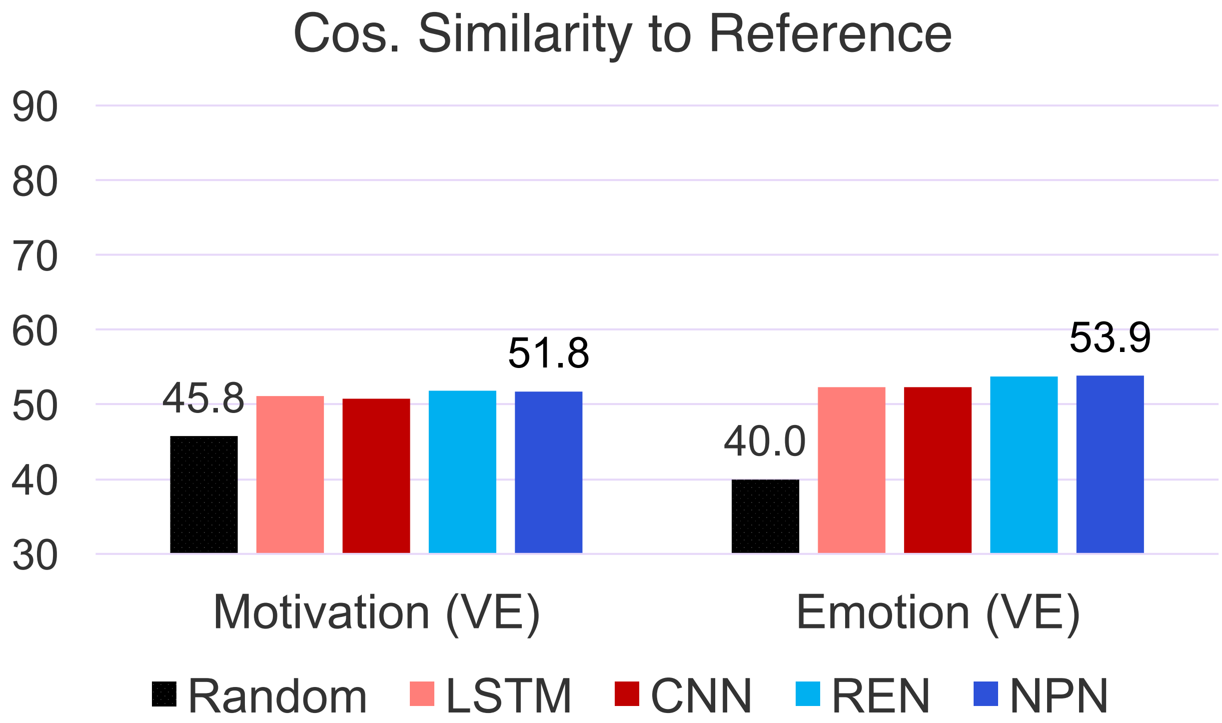
Explanation Generation Set-up

Evaluation: Cosine similarity of generated response to reference

Random baseline: Select random answer from dev set

- Responses are short/formulaic
- Words for describing intent/emotion are close in embedding space

Explanation Generation Results

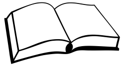


Task 2 – Mental State Classification

Predicting psychological categories for mental state

Input

The band instructor told the band to start playing.



Story Text Excerpt + Character

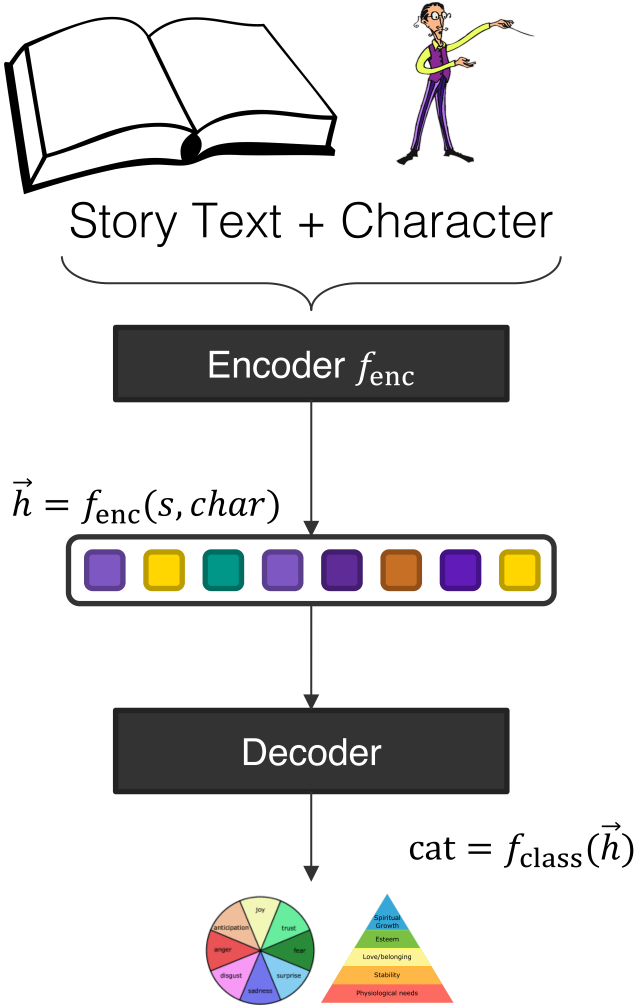
Output

anticipation

Theory categories

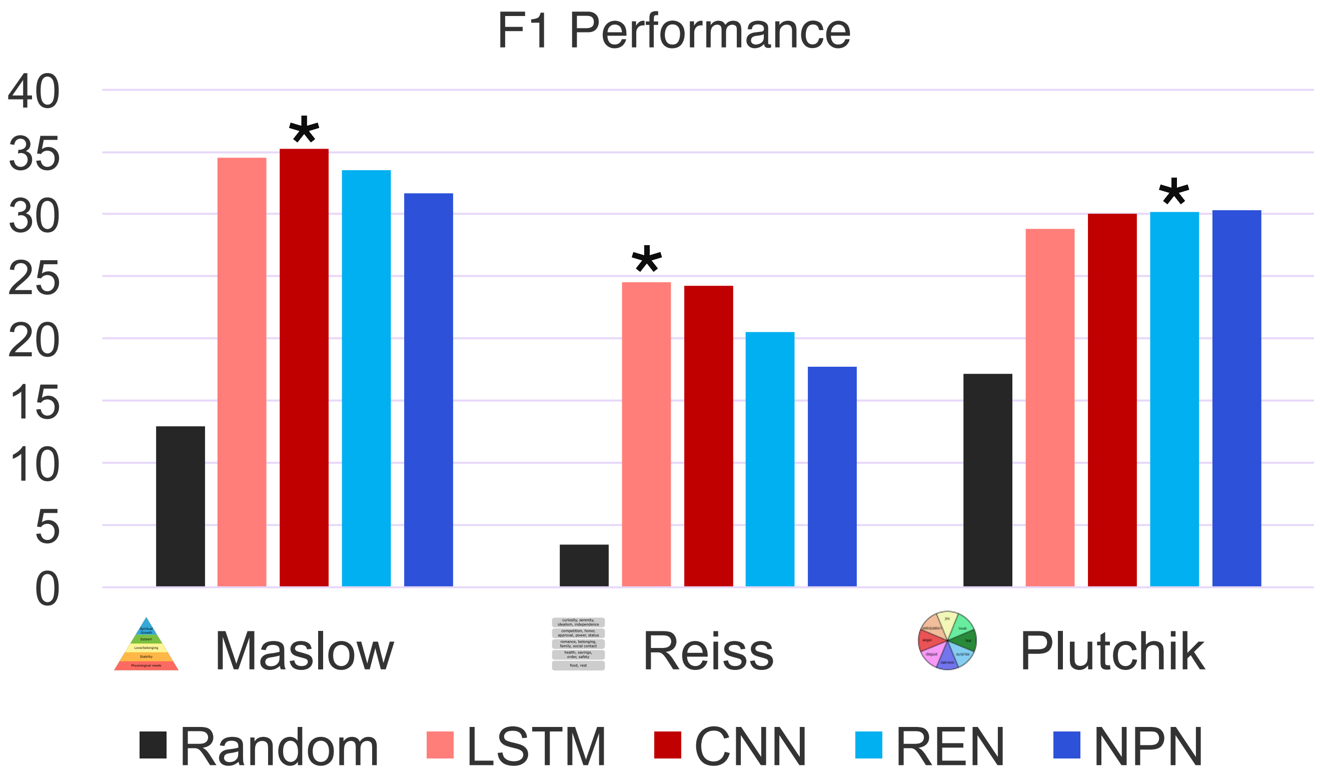
Modeling

- Using encoder-decoder framework
- Encoders - LSTM, CNN, REN, NPN
- Decoder for categorization: **logistic regression**



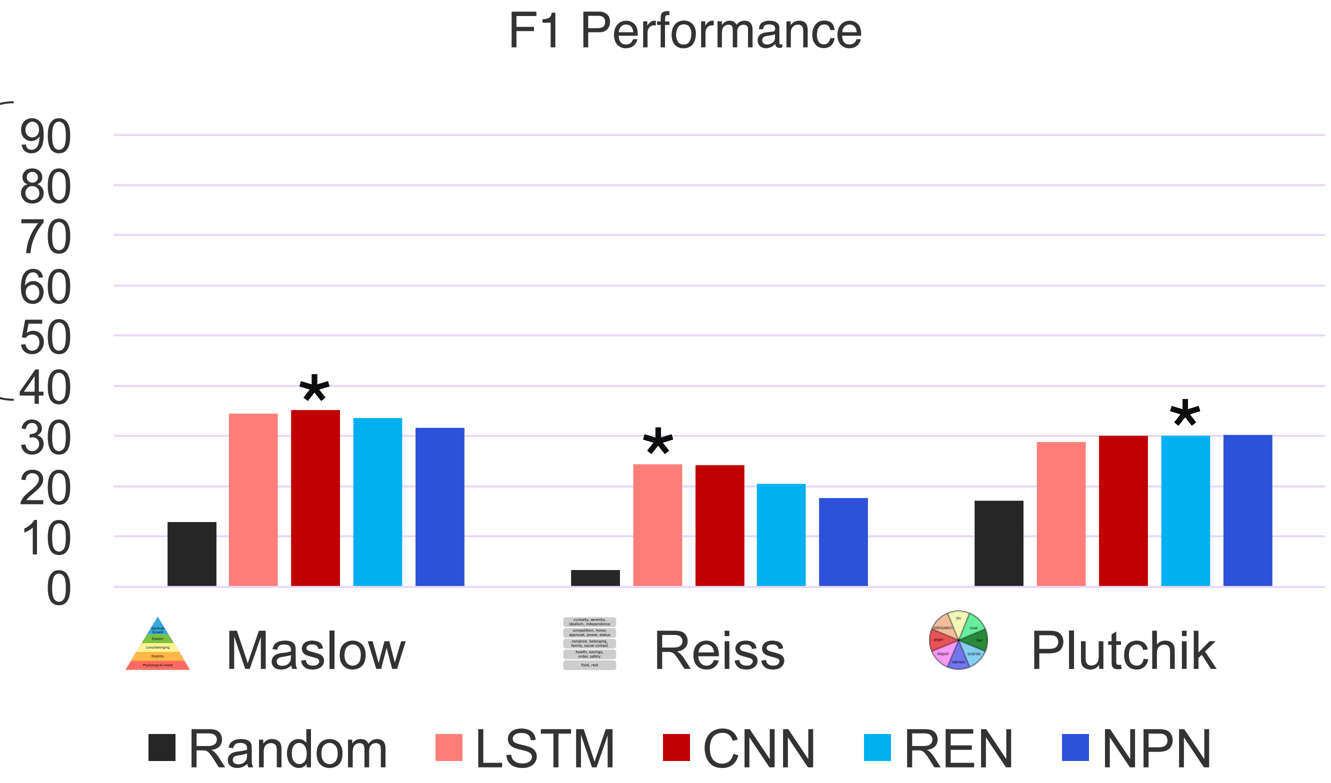
State Classification Results

- CNN and LSTM perform best on motivation categories
- Entity modeling has slight improvement in Plutchik



Further Improvement

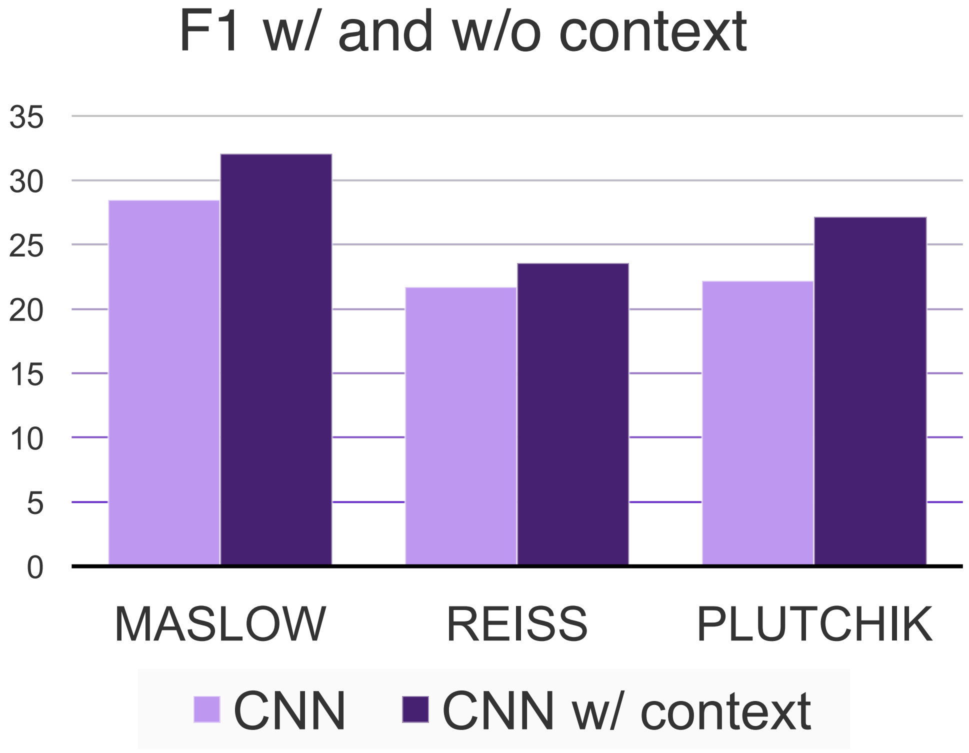
Best F1
at ~35%



Effect of Entity Specific Context

Including previous lines from context that include entity

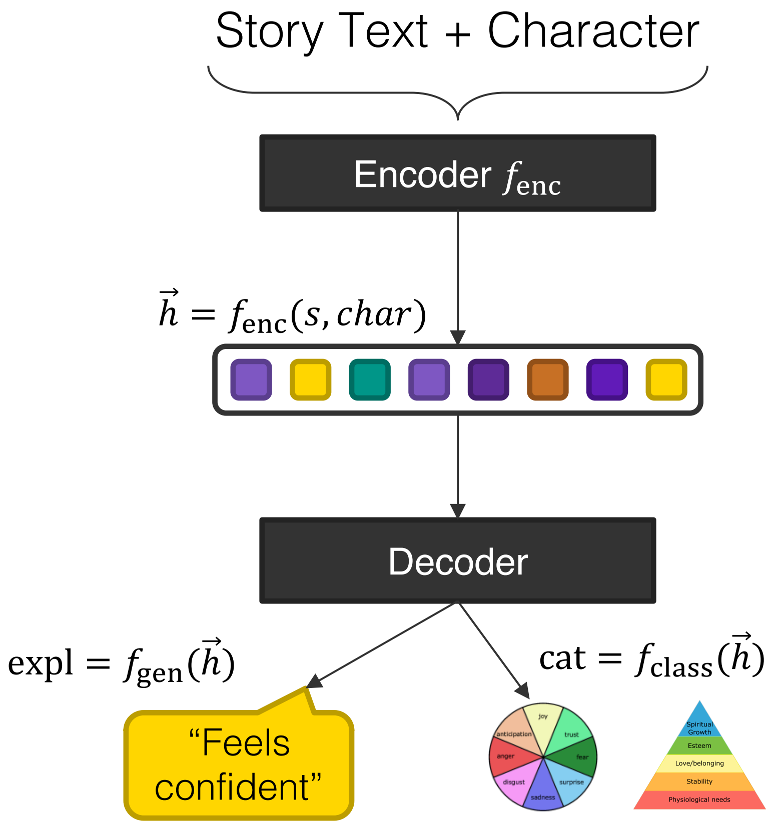
Entity specific context: improves all models F1 by about 3-5%



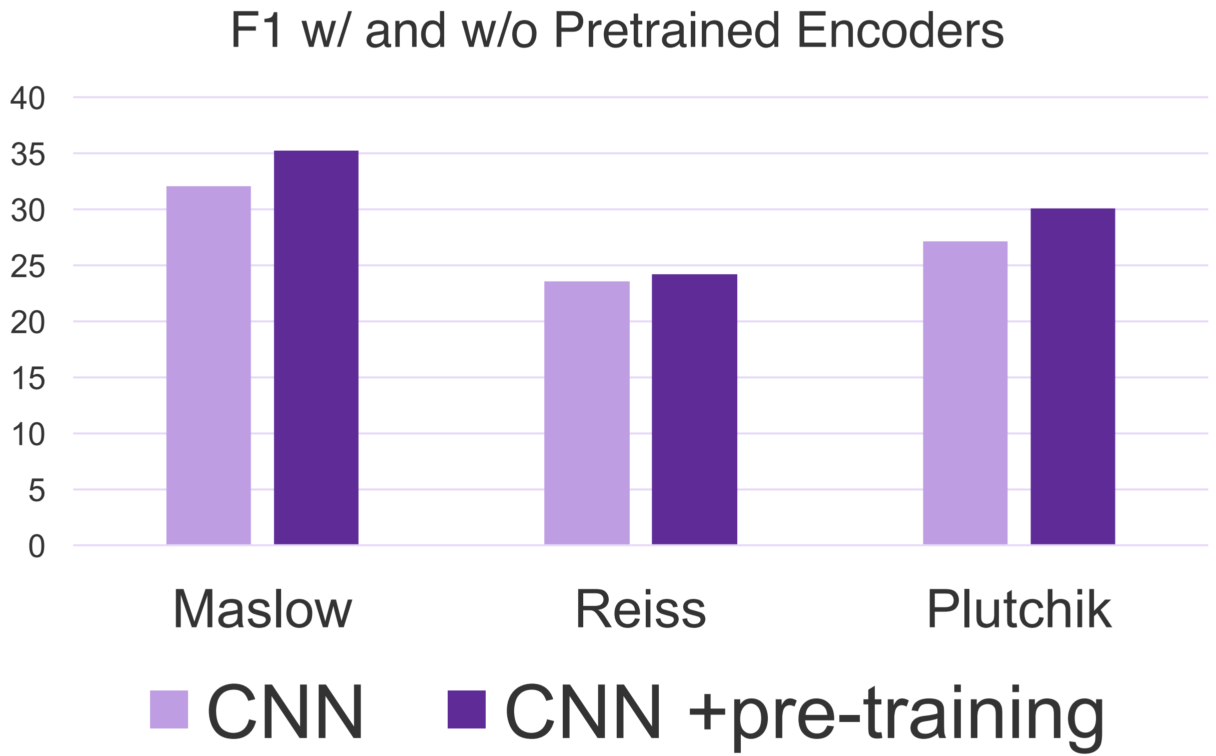
Pre-training Encoders

We have more open-text explanations than category annotations:

1. Pre-train encoders on open-text explanations
2. Fine-tune with the categorical labels



Effect of Pretrained Encoders

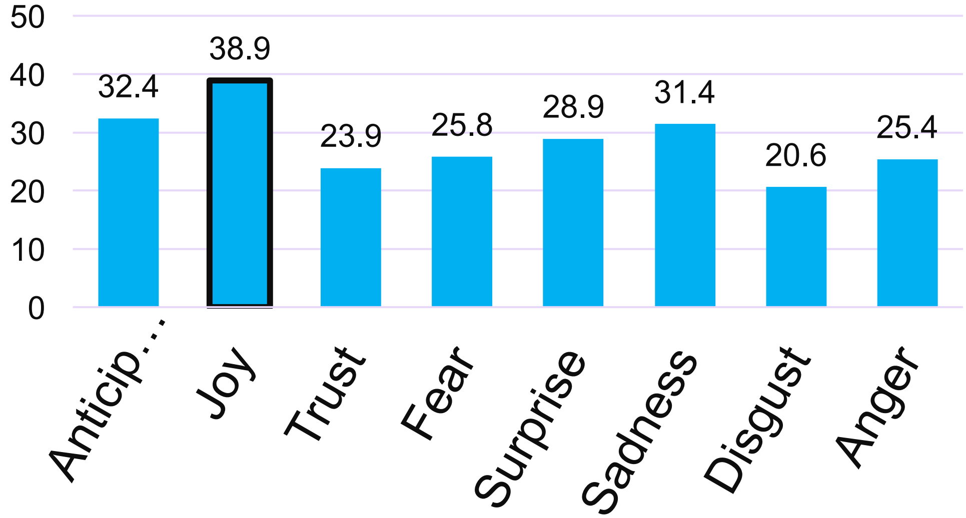


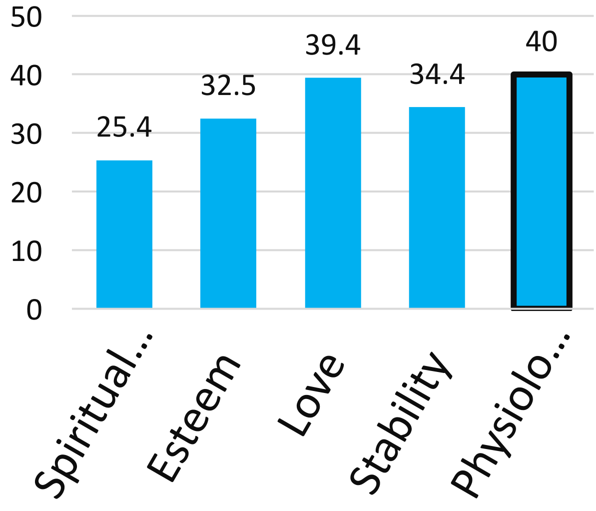
Improves:
1-2%

Performance Per Category

Highest performance:

- Frequent classes (eg. “joy” F1: 38.9%)
- Very concrete sets of actions (“physiological” F1: 40%)





Future Work

- **Outside Knowledge**: Help with infrequent classes and subtle implied changes

- **Social Commonsense**: Help with inferring mental state especially in more contextual cases

- **Potential Applications**: Improving language models, chat systems, natural language understanding

Conclusions

- New Dataset:
  - 15k roc stories annotated per character
    - >50k motivation changes
    - >100k emotions changes
  - `https://uwnlp.github.io/storycommonsense/`