

Help! Need Advice on Identifying Advice

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Parenting with a history of depression?

- ① I took my meds the whole time. I used the tools I learned in therapy. I talked on Reddit with others to get support and ideas.

(r/AskParents)

People often give advice **implicitly** using personal narratives and other strategies (Abolfathiasl et al. 2013).

Is it too late to start a hobby/activity at 12?

- ② ..you can always pick anything up you think is interesting and giving it a shot. You never know what you are good at until you try new things! Idk if you have a budget or maybe borrow tools but you can try woodworking? It's fun and frustrating (in a good way) at the same time

(r/needadvice)

Advice is often **interspersed** with support, reassurance and reasoning.

How do people give advice (online)?

Advice Questions Dataset of advice-seeking intentions from personal narratives (Fu et al. 2019).

Suggestion Mining SemEval-2019 introduced a pilot task on suggestion mining but suggestions are not synonymous with advice (Negi et al. 2019).

TuringAdvice A framework that evaluates language models by asking them to generate useful advice for humans (Zellers et al. 2020).

How is advice structured online?

This work aims to advance both our understanding of how people give advice, as well as to provide resources for learning to identify advice

How good are computational models at identifying advice?

We establish preliminary baselines with rule-based models (Negi et al. 2019, Potamias et al. 2019) and BERT (Devlin et al. 2019), and analyze their performance.

ANNOTATION PROTOCOL AND DATASET

DATA SOURCES

To model general online human advice-seeking interactions, we chose to construct datasets from Reddit forums (subreddits) focused on advice.

r/AskParents	r/needadvice
parents seeking advice	a general advice forum
less moderation	more moderation
no flairs	5 flairs – “Education”, “Career”, “Mental Health”, “Life Decisions”, “Friendships”

ANNOTATION

1 Reply 1

3 In Kentucky it 's legal to leave a " mature " 8 year old at home alone all day .

4 I find that crazy young .

8 I started leaving mine home at age 9 - 10 for a half hour here , 45 min there , working up to a couple of hours .

10 >>>> Reply 1.1

12 Yeah , even though my son has always been very mature for his age , I would not have been comfortable leaving him home alone all day long at age eight !

14 -----

16 Reply 2

18 For an hour ?

19 I 'd on average say elementary school aged .

20 So 6 up , depending on how responsible / mature the child is and if they 're willing to stay home alone .

22 No answering the door , no leaving the house , no using the stove , no friends over and I 'd talk about what neighbors might be home in case of an emergency .

24 Oh , and I 'm from Germany .

ANNOTATION

1	Reply 1
	Advice
3	In Kentucky it 's legal to leave a " mature " 8 year old at home alone all day .
4	I find that crazy young .
	Advice
8	I started leaving mine home at age 9 - 10 for a half hour here , 45 min there , working up to a couple of hours .
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12	Yeah , even though my son has always been very mature for his age , I would not have been comfortable leaving him home alone all day long at age eight !
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18	For an hour ? I 'd on average say elementary school aged . So 6 up , depending on how responsible / mature the child is and if they 're willing to stay home alone .
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22	Oh , and I 'm from Germany .

5 annotators on Amazon Mechanical Turk annotated each HIT of 5 comments.

We chose **sentences** as the units of advice.

How to aggregate sentence labels while accounting for inter-annotator variability?

Dawid-Skene Labels

An EM based algorithm that estimates the label with the maximum estimated **posterior probability** by iteratively computing annotator competencies and type probabilities (Dawid et al. 1979).

DATASET

r/AskParents 10,594 sentences 407 posts

r/needadvice 7,862 sentences 277 posts

Data (and code) available at

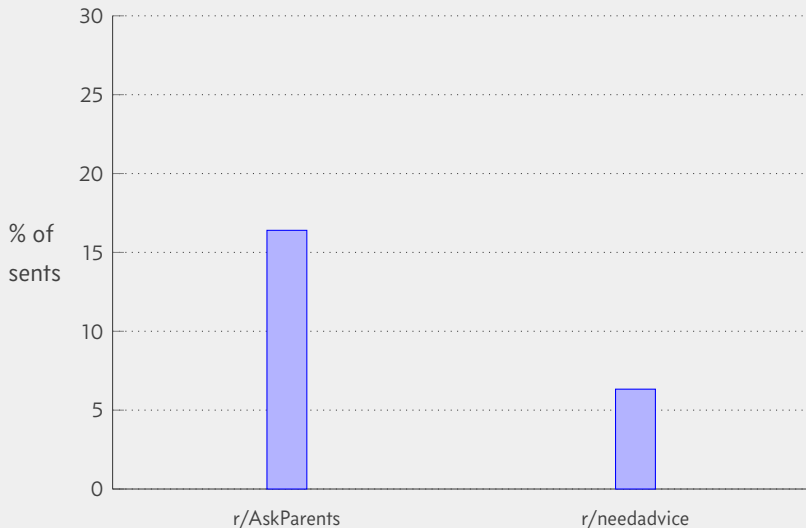
[GITHUB.COM/VENKATASG/ADVICE-EMNLP2020](https://github.com/VenkatasG/Advice-EMNLP2020)

ADVICE STRATEGIES

- ③
 - a. I did the classic Ferberizing: check on baby after 5 mins, then 10 mins, then 20 mins, etc, until asleep. **PERSONAL NARRATIVE**
 - b. Have you tried a calm spray? **QUESTIONS**
 - c. Figure out why they like them , and then recommend those ones for those reasons. **IMPERATIVES**
 - d. If he doesn't want therapy, maybe an antidepressant would help. **CONDITIONALS**

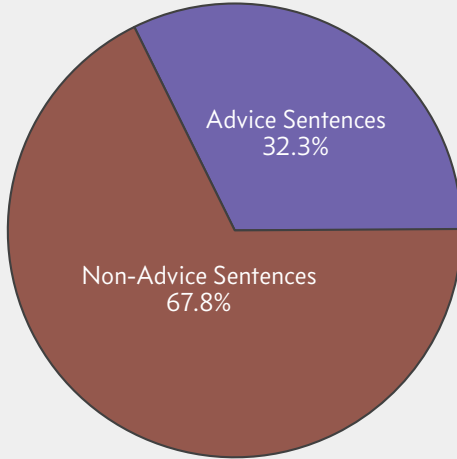
To study personal narratives further, we (the authors) analyzed 213 sentences DS-labelled as advice for whether they contained personal narratives.

PERSONAL NARRATIVES



Y Axis shows % of sentences that were judged to contain personal narratives.

NON-ADVICE



Proportion of advice and non-advice in our dataset

- ④ a. ...being fully prepared for an interview calmed me down ... **Good luck on your interviews and fingers crossed.** SENTIMENT
- b. Look for smaller outfits, they're more likely to be willing to give you some time. **Most professionals - if they have the time - are more than happy to talk to a student about what they do...** SUPPORT
- c. **Yes, no one will ever know the big answers to the big questions.**
What is the only thing that if shared , will grow larger in size?
Answer: Love. Let that define your actions in life. REASONING

LEXICAL ANALYSIS

	Advice	Non-advice
r/AskParents	book if take something help then you might talk need down can etc play find show or great also give buy big watch diaper car about else minute spend baby	luck sorry shit however dog crazy teenager op die eventu- ally three wish weird daugh- ter yeah brother example miss gender anyway anymore com- ment morning lol boyfriend girl younger hope drive mine
r/needadvice	he phone night adult stay set big game doctor fun bring less show love depend activity eat normal put teacher family etc minute teach allow home they area	luck degree company college interview hobby student field mental course op sorry job dog anxiety hire eventually position path shit comment human online community shoe thanks note exercise depression slowly

MODELING

We model advice identification as a **binary classification task**.

Rule-based SEMEVAL 2019 baseline & NTUA-IS 2019^(Potamias et al. 2019).

Match and score against **words**, **phrases**, **regexs**:

*suggest, recommend, .*would\slike.*if.**

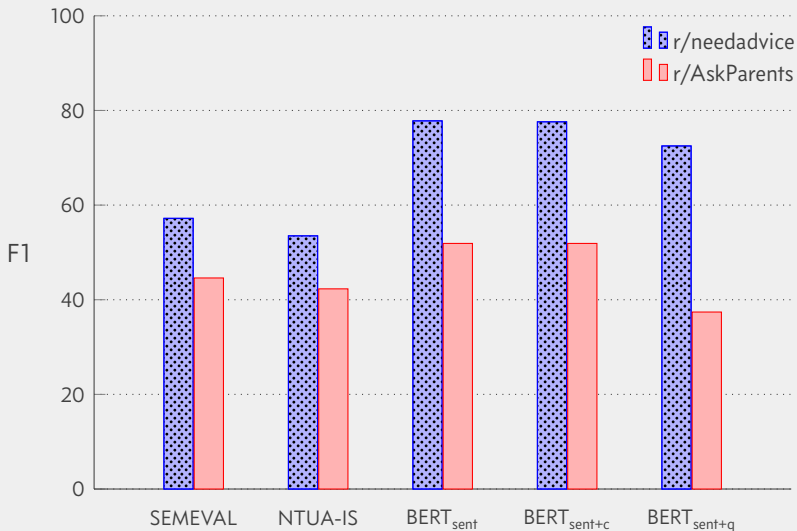
Language Models We use **BERT** ^(Devlin et al. 2019) and experiment with input:

BERT_{sent} [CLS] SENTENCE [SEP]

BERT_{sent+q} [CLS] SENTENCE [SEP] QUESTION

BERT_{sent+c} [CLS] SENTENCE [SEP] CONTEXT

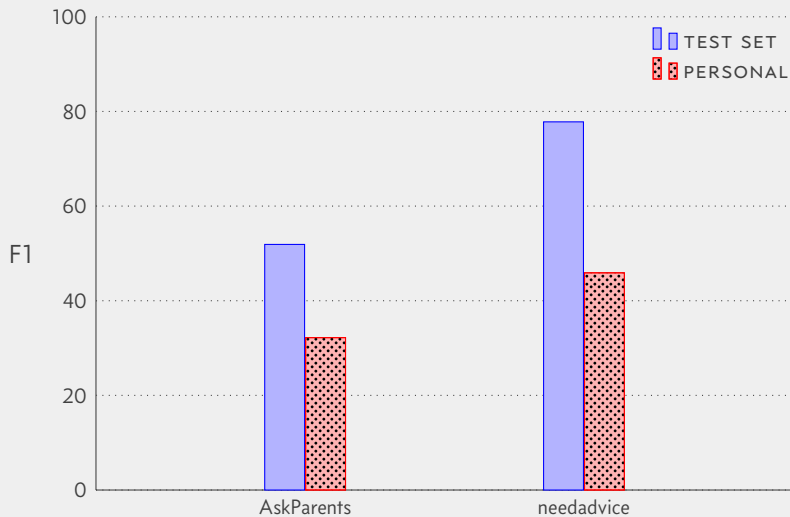
RESULTS



$BERT_{sent}$ has best performance.

Performance on $r/AskParents$ worse than $r/needadvice$

PERFORMANCE ON PERSONAL NARRATIVES



BERT_{sent} performance on personal narrative sentences in test set suffers.

Dataset We introduce a new dataset for **advice given online**.

Advice Structure People use various **strategies** when giving adviceaa.

Modeling Language models learn some surface-level rules, but need to do better at **implicit advice**.

REFERENCES

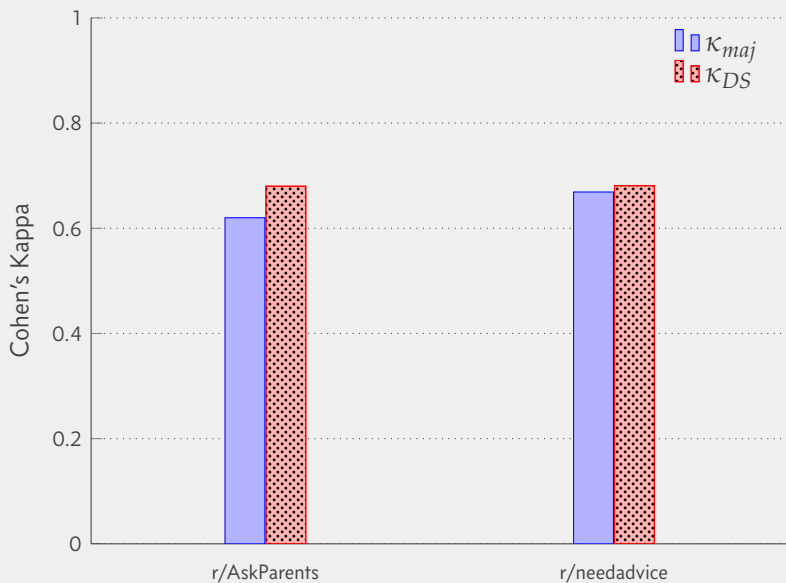
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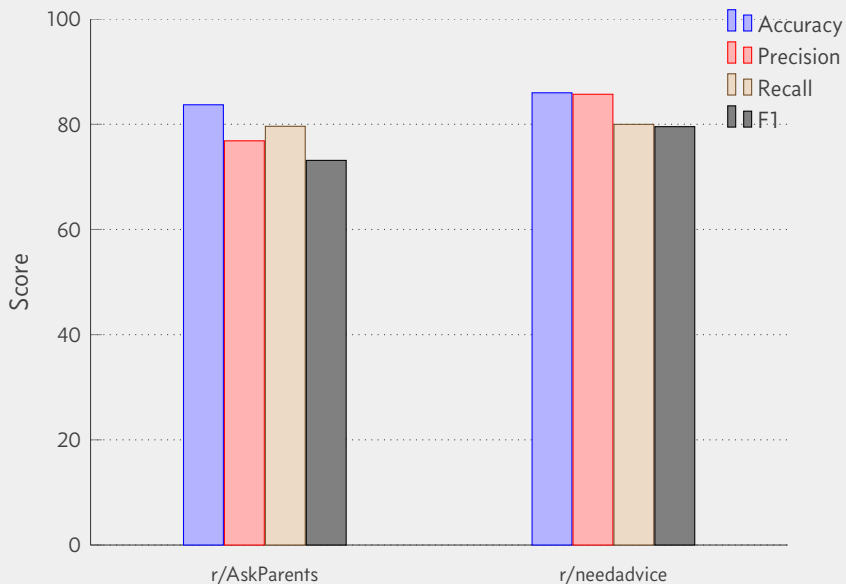
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APPENDIX

GOLD ANNOTATOR AGREEMENT



AVERAGE INTER-ANNOTATOR AGREEMENT



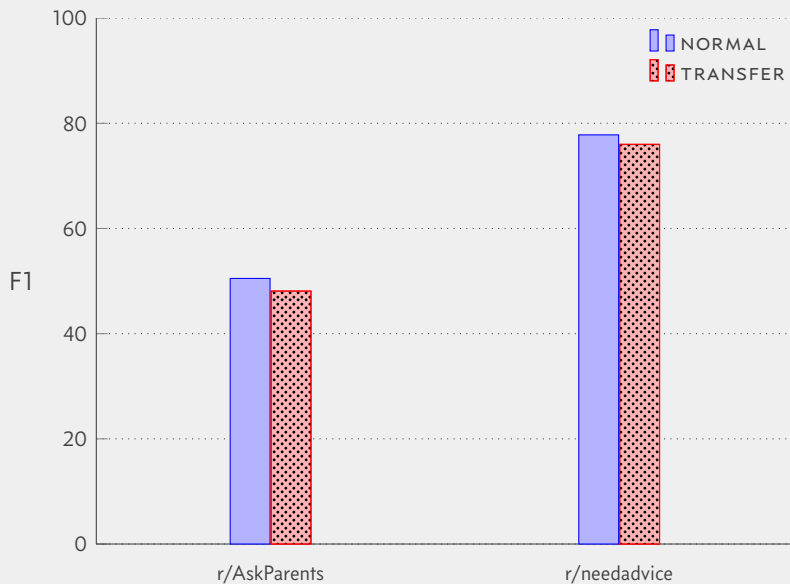
LEXICAL ANALYSIS

We quantify how strongly individual lemmas are associated with advice versus non-advice text using the log-odds ratio (Nye et al. 2015).

$$Odds(w, c) = \frac{P(w|c)}{1 - P(w|c)} \quad (1)$$

$$\text{log-odds ratio} = \frac{Odds(w, advice)}{Odds(w, non - advice)} \quad (2)$$

GENERALIZABILITY RESULTS



DATASET METRICS

Dataset	Train	Dev	Test
AskParents	8701(.29)	802(.33)	1091(.26)
needadvice	6148(.37)	816(.34)	898(.37)

Sentence metrics in our dataset, with fraction DS-labeled as advice.

GOLD INTERNAL AGREEMENT

Dataset	Sentences	κ_{maj}	κ_{DS}
AskParents	203	0.620	0.669
needadvice	110	0.680	0.681

Gold annotator agreement on the internal task.

AGREEMENT

Dataset	Acc	P	R	F1
AskParents	83.71	76.86	79.62	73.14
needadvice	85.99	85.71	79.99	79.55

Average inter-annotator agreement for all workers against DS labels

DISCOURSE MODES

Subreddit	Other (%)	Personal Narrative (%)
r/AskParents	83.6	16.4
r/needadvice	93.67	6.33
-Career	100	0
-Mental Health	81.82	18.18
-Friendships	100	0
-Education	95.4	4.6
-Life Decisions	88.9	11.1

Modes of discourse for advice sentences in each flair/subreddit

RESULTS-CLASSIFICATION

	Model	P	R	F1
r/AskParents	SEMEVAL	32.7	70.2	44.6
	NTUA-IS	31.4	64.9	42.3
	BERT _{noff}	62.6 (1.2)	14.9 (1.0)	24.0 (1.4)
	BERT _{sent}	54.9 (2.4)	49.5 (4.4)	51.9 (1.9)
	BERT _{sent+c}	54.2 (2.1)	49.9 (4.0)	51.9 (2.2)
	BERT _{sent+q}	61.0 (13.4)	33.1 (11.9)	37.4 (8.1)
r/needadvice	SEMEVAL	44.5	80.3	57.2
	NTUA-IS	43.0	70.9	53.5
	BERT _{noff}	82.9 (0.5)	44.6 (1.4)	58.0 (1.2)
	BERT _{sent}	79.7 (3.8)	76.3 (3.9)	77.8 (0.3)
	BERT _{sent+c}	80.4 (4.4)	75.3 (4.4)	77.6 (0.7)
	BERT _{sent+q}	83.4 (4.8)	64.7 (7.4)	72.5 (3.5)

Classification results on test set.

RESULTS-GENERALIZATION

Model	P	R	F1
AP \rightarrow AP	54.9 (2.4)	49.5 (4.4)	51.9 (1.9)
AP _p \rightarrow AP	59.1 (3.5)	44.4 (4.1)	50.5 (1.8)
NA \rightarrow AP	61.9 (4.9)	39.7 (3.5)	48.1 (1.3)
NA \rightarrow NA	79.7 (3.8)	76.3 (3.9)	77.8 (0.3)
AP \rightarrow NA	74.0 (4.0)	79.3 (2.9)	76.5 (0.9)
AP _p \rightarrow NA	76.9 (3.8)	75.5 (4.7)	76.0 (1.1)

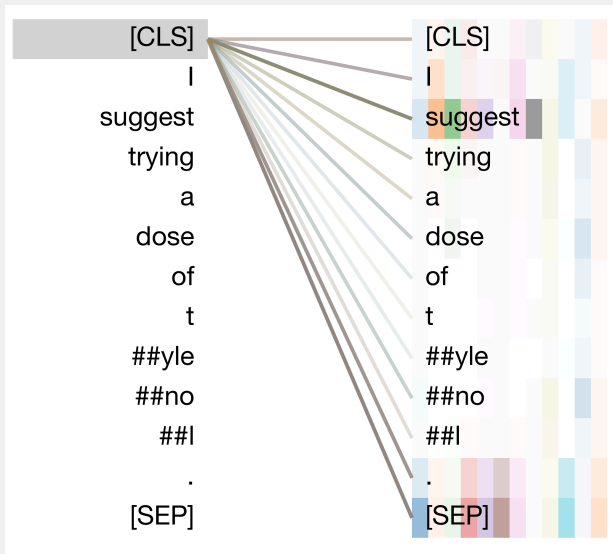
Generalizability results on test set.

RESULTS-FLAIR

Flair	P	R	F1
Friendships	85.5 (5.7)	93.8 (0.0)	89.2 (2.9)
Mental Health	75.6 (3.5)	74.7 (3.6)	75.0 (0.6)
Education	86.8 (2.9)	67.4 (6.2)	75.7 (3.1)
Career	75.9 (5.1)	78.0 (3.8)	76.7 (1.3)
Life Decisions	82.4 (4.4)	82.8 (3.5)	82.4 (0.7)

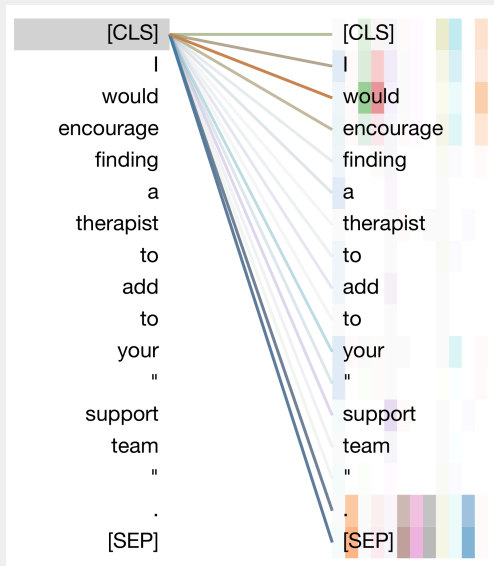
Flair results on test set.

ATTENTION



Attention weights visualized using BertViz (Vig 2019)

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