A Pretrained Language Model for Mental Health Risk Detection

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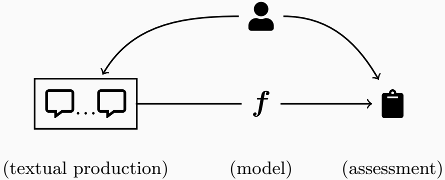
UQÀM

Background

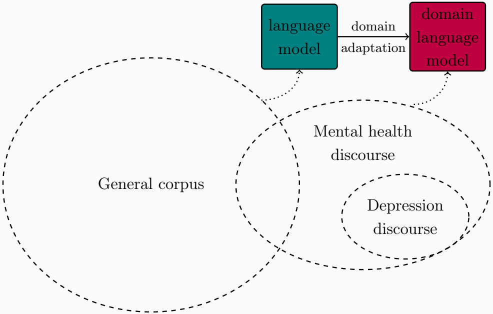
- Increased interest in early intervention in mental health care [Schotanus-Dijkstra et al., 2017, McGorry and Mei, 2018].
- Ever-growing use and diversity of online social media → research interest for automated analysis of online textual content for mental health care support [Shing et al., 2020, Maupomé et al., 2021].



- Annotation is expensive, semi-supervised learning is needed

Motivation

- Large models trained over large datasets perform better.
- Computation amortized by versatility.
- Some **domain adaptation** is needed: what does this mean in mental health?
- Idea: compare models pretrained on specific vs. general corpora.



Pretraining data

Pretraining data extracted from separate fora: `AnorexiaNervosa`, `depression`, `selfharm`

	`AnorexiaNervosa`	`depression`	`selfharm`
Tokens	3.7G	160.9G	18.8G
Vocabulary	38.4k	303.2k	87.1k
Posts	10.3k	412.4k	78.0k
average number of tokens	141	204	116
Comments	45.8k	1404.3k	236.4k
average number of tokens	49	54	41
Unique authors	10.1k	338.1k	43.3k
Community size*	23.8k	736k	66.4k

Subreddits statistics. Unique authors exclude deleted accounts. *As of March 2nd 2021.

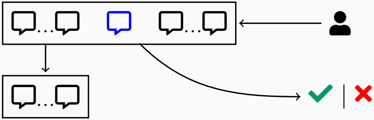
Pretraining process

- Based on RoBERTa [Liu et al., 2019]
- Adapt models with single set
- What role does tokenization play? Train "blank" models with tokens learned from joint data, separate data

Evaluation

Risk detection (binary) with eRisk datasets

[Losada et al., 2018, Losada et al., 2019, Losada et al., 2020]



dataset	Train		Test	
	positive	negative	positive	negative
Depression	214	1493	98	1302
Self-Harm	145	618	152	1296
Anorexia	61	411	73	742

Evaluation

- Building the classifier:
  - Document encoding: average tokens from post, feed-forward network
  - Average document vectors together
  - Training: contiguous sample of 50 posts, Test: last 50 posts
- Addressing class imbalance:
  - Inverse class weighting, effective sample weighting [Cui et al., 2019] and Focal Loss [Lin et al., 2018] proved ineffective
  - Even batches worked best
- Details:
  - Only two top layers of Transformer
  - Adam over ten epochs

Results

Baselines:

- General-purpose language model: RoBERTa [Liu et al., 2019]
- Mental health domain-adapted model: MentalRoBERTa [Ji et al., 2022]

	Tokenization	Depression	Self-Harm	Anorexia
RoBERTa	RoBERTa	0.487	0.434	0.401
RoBERTa with domain adaptation	RoBERTa	0.496	**0.494**	0.555
MentalRoBERTa	RoBERTa	0.536	0.476	0.416
MentalHealthBERT	Separate	**0.520**	0.475	0.560
MentalHealthBERT	Combined	0.457	0.485	**0.569**

Area under the precision-recall curve on the eRisk test sets

Takeaways

- Domain-specific pretraining helps
- No real difference between blank and adapted models
- Mitigated results for more specific pretraining
- Future work:
  - Which disorders combine well in pretraining?
  - Does this relate to their theoretical relationship?
  - Would this be entirely attributable to topics?
  - Additional tasks

THANK YOU

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