Exploring Amharic Sentiment Analysis from Social Media Texts
Building Annotation Tools and Classification Models

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ABSTRACT

This work deals with sentiment analysis for Amharic social media texts. Social media users are ever-increasing, however, low-resource languages such as Amharic have received less attention due to 1) lack of **well-annotated datasets**, 2) unavailability of **computing resources**, and 3) fewer or no **expert researchers** in the area.

Research questions and approaches:

- Explore the suitability of existing tools for the sentiment analysis task. We build a social-network-friendly annotation tool called 'ASAB' using the Telegram bot and collect 9.4k tweets.
- Explore the suitability of machine learning approaches for Amharic sentiment analysis. The FLAIR deep learning text classifier, based on network embeddings that are computed from a distributional thesaurus, outperforms other supervised classifiers.
- Investigate the challenges in building a sentiment analysis system for Amharic. We found that the widespread usage of sarcasm and figurative speech are the main issues in dealing with the problem.

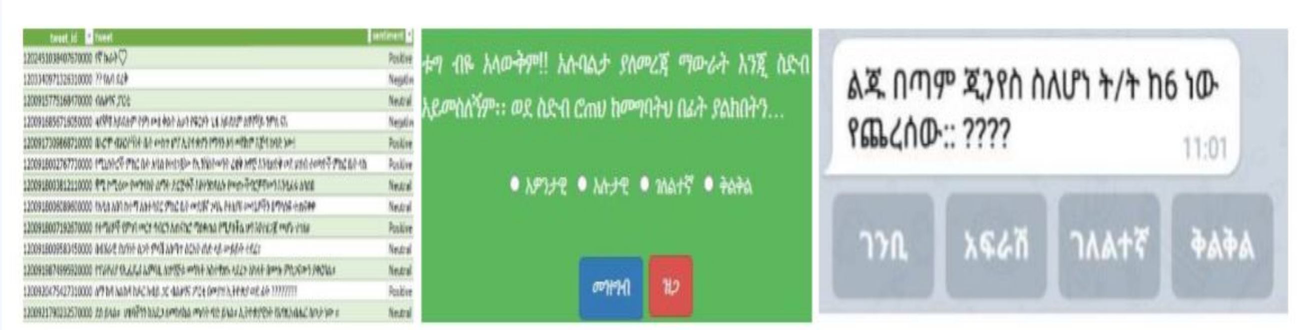
MOTIVATION

- Social media data is increasing but:
  - Lack of standard datasets.
  - Lack of basic NLP tools.
  - Lack of annotation tools and platforms.
  - Complex nature of Amharic .
- Hence, we need to build an **annotation tool**, annotate the data, and build models, enable applications to capture opinions from a social media text.

OBJECTIVE

- Exploring different annotation strategies and tools for low-resource languages.
- Annotating a large dataset.
- Build different machine learning models.

DATA COLLECTION TOOLS



(a) Excel-sheet for annotation (b) Web annotator interface (c) ASAB interface

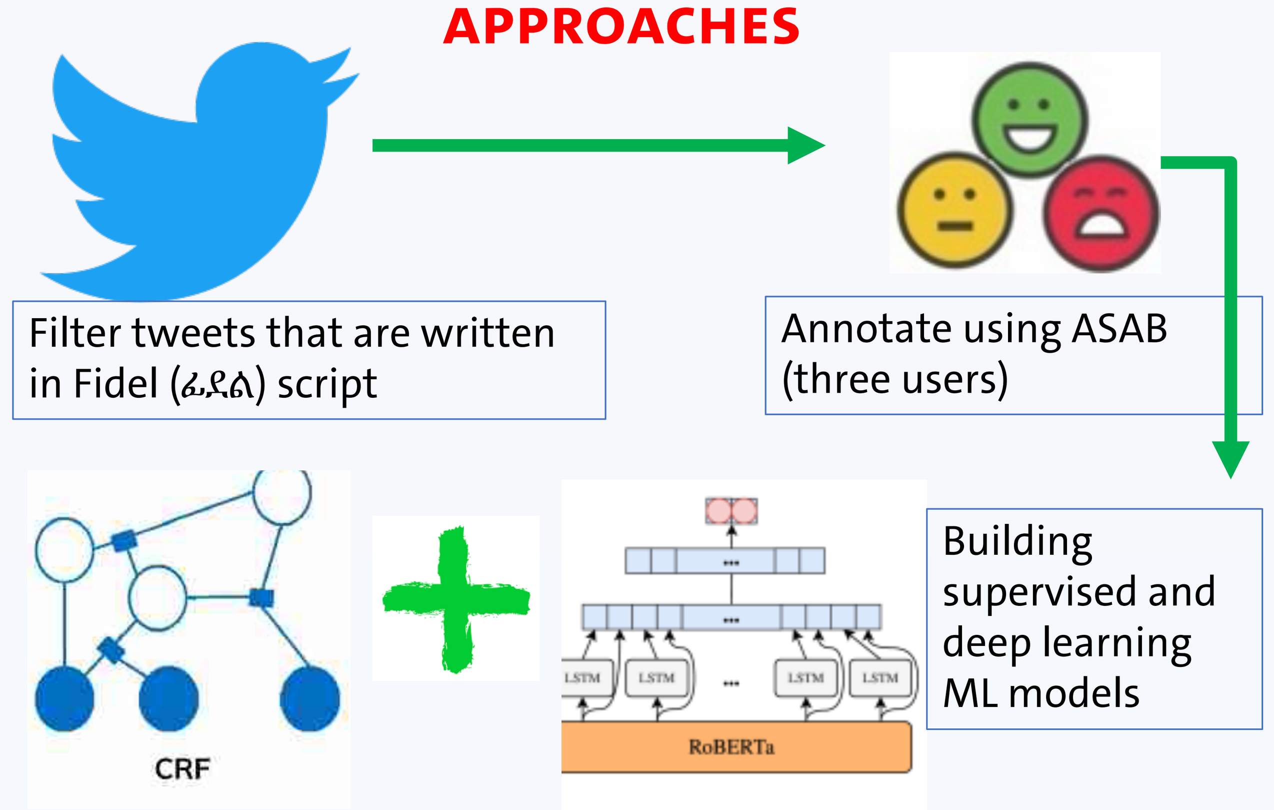
AMHARIC SENTIMENT ANNOTATOR BOT (ASAB)

- ASAB support mobile card vouchers rewards for annotators.
- Reward given when a user annotates 50 tweets.
- ASAB integrates a controlling control questions for every 6 tweets.
- A users with 3 consecutive mistakes will receive a warning message.
- User blocked after the fourth wrong attempt.

MACHINE LEARNING MODELS

- Baseline methods:
  - Stratified, Uniform, and Most frequent.
- Supervised approaches:
  - SVM, KNN, Logistic regression, Nearest centroid
  - Features: **TF-IDF** with the **CountVectorizer** and **TFIDFTransformer** methods from scikit-learn.
- Deep learning approaches:
  - Models based on FLAIR deep learning text classifier.
  - Features: Word2Vec, network embeddings, contextual embeddings (**RoBERTa** and **FLAIR** embeddings)

APPROACHES



DATA ACQUISITION AND DATASET CHARACTERISTICS

- Data Source: Ethiopic Twitter Dataset for Amharic (ETD-AM) Yimam et al. (2019).
- Data collected: December 2019 - January 2020.
- Political and social events happening:
  - The current Ethiopian Prime Minister Dr. Abiy Ahmed has received the 100th Nobel peace prize.
  - Around 17 university students were kidnapped.
  - The ruling party EPRDF was resolved and transformed itself to 'prosperity party'.
  - Religious and ethnic conflicts reached climax.

RESEARCH OUTPUTS

- Dataset
- Annotation tool
- Pre-trained models
- Source code

CONTACT/RESOURCE

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https://github.com/uhh-lt/ASAB

RESULTS AND ANALYSIS OF ANNOTATED DATA

- 9.4k tweets annotated (143,848 words and 45,525 types), each tweet three annotators.
- A total of 92 Telegram users visited ASAB.
- 58% of users completed at least 50 tweets and got rewarded.
- 4 users blocked for consecutive mistakes.

Model	All				Cleaned			
	Accuracy	Precision	Recall	F1	Accuracy	Precision	Recall	F1
	TF-IDF representation							
Logistic-Regression	53.04	34.76	39.99	37.19	58.42	46.80	60.88	52.92
Random-Forest	50.48	33.97	37.75	35.76	54.36	44.59	52.17	48.09
K-Nearest-Neighbor	46.75	34.99	33.53	34.25	51.68	49.85	50.22	50.03
NearestCentroid	42.07	35.96	37.61	36.77	51.92	47.36	49.20	48.26
Support-vector-machine	52.40	33.54	41.81	37.22	53.19	35.44	46.42	40.20
	Word Embeddings							
fastText	49.63	36.26	35.08	35.66	54.12	48.35	51.33	49.79
F-Word2Vec	53.57	**41.76**	43.01	**42.38**	55.40	55.54	54.91	55.22
F-fastText	51.22	31.96	51.80	39.53	56.68	43.50	67.81	53.00
	Contextual Embeddings							
F-AmharicFlair	53.04	38.66	45.85	41.95	58.65	53.24	59.25	56.09
F-Multi-flair	53.67	36.41	41.89	38.96	55.75	46.96	55.05	50.68
F-Multi-flair-Finetuned	54.42	38.10	**45.87**	41.63	59.81	54.49	59.58	56.92
Amharic-Roberta	53.89	40.05	39.71	39.88	56.33	46.62	56.39	51.04
	Graph Embeddings							
F-DeepWalk	**54.53**	38.49	41.08	39.74	58.65	55.89	57.71	56.78
F-Role2Vec	52.40	39.45	41.16	40.29	**60.51**	**56.26**	**60.89**	**58.48**
	Baselines							
Stratified	34.72	26.59	26.71	26.65	39.02	33.79	33.80	33.80
Uniform	23.54	24.19	23.69	23.94	30.89	29.72	30.96	30.33
Mostfrequent	47.60	25.00	11.90	16.13	51.92	33.33	17.31	22.78

ERROR ANALYSIS

- We randomly select tweets where the model prediction and the user annotations differ.
- Possible source of errors:
  - Users press the wrong button by mistake.
  - Some users might not understand the tweet.
  - Due to slow internet connection, some users reported that there was a delay between the first and the second tweet.
  - Sarcasm, figurative speech, mixed scripts, incomplete phrases and sentences, and spelling and grammar errors cause most of the model errors.