Graph Convolutional Network for Swahili News Classification

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Graph Neural Networks Introduction Swahili is an under-represented language in NLP research A corpus contains an implicit Annotated datasets and accessible benchmarks. graph structure: · Techniques developed for high-resource languages may not · Semantic and syntactic $h_i =$ transfer to a low-resource context relationships Purpose-built tools and libraries Semi-supervised learning: Aggregate information from Semi-Supervised Swahili News Classification a neighbourhood of nodes Semi-supervised context is applicable in low-resource NLP Label sparsity Swahili News Classification Dataset (David, 2020) Figure 2: Visualisation of the 1-hop neighbourhood used Key features and contributions: to update the hidden state of the red reference node Set of accessible benchmarks • First application of Graph Neural Networks (GNNs) on an African language Memory efficient variant of Text Graph Convolutional Results Network (Yao, 2019) Semi-supervised node classification 6 news categories **Baselines** 20% of the training set is labelled Traditional NLP benchmarks Text GCN variants surpass baseline performance TF-IDF Text GCN-t2v is cheaper and faster to train Counts Averaged fastText embedding (Bojanowski, 2017)

- PV-DBOW (Le, 2014)
- PV-DM (Le, 2014)



Figure 1: High-level overview of the baseline model pipeline.



Figure 3: Reducing the number of labels in the training set

Text GCN

15.0 17.5 20.0

Text GCN-t2v TF-IDF Counts

Results

Conclusion

- Text GCN for semi-supervised Swahili news classification outperforms traditional methods
- Representing a corpus as a graph
- Future work:

Alternative graph representations and inductive GNN

References

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Model	Accuracy (%)	Macro F ₁ (%)
TF-IDF	83.07 ± 0.00	68.72 ± 0.00
Counts	83.32 ± 0.00	73.60 ± 0.00
fastText	67.47 ± 0.00	32.41 ± 0.00
PV-DBOW	81.64 ± 0.47	72.93 ± 0.75
PV-DM	77.01 ± 0.38	67.50 ± 0.64
Text GCN	84.62 ± 0.10	75.29 ± 0.52
Text GCN-t2v	$\textbf{85.40} \pm \textbf{0.22}$	$\textbf{75.67} \pm \textbf{0.90}$

Table 1: Mean and standard deviation test set comparisons