

# Nearest neighbour approaches for Emotion Detection in Tweets

### Introduction

- This is a classification task **SemEval-2018 Task 1** *"Affect in Tweets"* for English tweets labeled with *emotions' intensity* (anger, sadness, joy, fear).
- We aimed to use the *interpretable* Machine Learning (ML) method (the **weighted k Nearest Neighbor** (wkNN)) to compete with *Neural Networks* (NN) based solutions.

## Experiments

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- We examined five *text embedding* approaches' performances by tuning the best *text preprocessing* and the number of neighbours **k** for the wkNN model for each. As a similarity function for the wkNN, we used **cosine**. Moreover, we used Pearson Correlation Coefficient (**PCC**) for evaluation.
- To improve results, we appended scores from emotional lexicon vocabularies to the embedding vectors.
- Finally, we made the **ensemble** of *the best* embedding models with the tuned voting function applied to the models' outputs and selected embeddings to use. Our final solution is illustrated in *Picture 1*.



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Results for the test data We checked our solution on the test data (PCC decreased compared with train) and submitted predicted labels to the competition page - we received fourth place with PCC = 0.635 (*Table 1*), where top-3 solutions were NN-based. We evaluated several test tweets manually to examine the solution's explainability and found some patterns (*Picture 2*).

Conclusion and the future work We evaluated the *explainable ML* method for the emotion detection and showed optimizations and ensemble method *can compete* with NN solutions. In the future, we plan to incorporate another method for an **unbalanced** fear dataset and consider the inherently **fuzzy nature** of emotion data.

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				Table 1. Winners	
Team	Average PCC	Anger	Fear	Joy	Sadness
#1	0.695	0.706	0.637	0.720	0.717
#2	0.653	0.670	0.588	0.686	0.667
#3	0.646	0.667	0.536	0.705	0.673
#4 (we)	0.635	0.638	0.601	0.631	0.670



