### Classification of texts by neural networks.

In my final project, I used neural networks to determine the topics of news from the <u>AG's News Topic Classification Dataset</u>. AG is a collection of more than 1 million news articles. News articles have been gathered from more than 2000 news sources by ComeToMyHead in more than 1 year of activity. ComeToMyHead is an academic news search engine which has been running since July, 2004. The dataset is provided by the academic comunity for research purposes in data mining (clustering, classification, etc), information retrieval (ranking, search, etc), xml, data compression, data streaming, and any other non - commercial activity.

I built 3 NN models: 1D Convolutional neutral network, LSTM and GRU neural networks. And compared their performance on test date set.

**First,** we start with getting training data and text tokenization. Text tokenization is the process of breaking down a given text into smaller units called tokens. These tokens can be individual words, characters, or subwords, depending on the specific tokenization technique used.

#### From now we can build our NN models. Here is what they look like.

```
Convolutional Neural Network
model_cnn = Sequential([
    Embedding(num_words, 32, input_length=max_news_len),
    Conv1D(250, 5, padding='valid', activation='relu'),
    GlobalMaxPooling1D(),
    Dense(64, activation='relu'),
    Dropout(0.2),
    Dense(32, activation='relu'),
```

```
Dropout(0.2),
Dense(4, activation='softmax')])
```

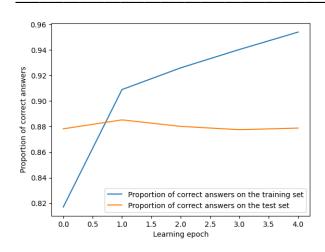
model\_cnn.summary()

Model: "sequential\_9"

Output Shape	Param #
(None, 30, 32)	320000
(None, 26, 250)	40250
(None, 250)	0
(None, 64)	16064
(None, 64)	0
(None, 32)	2080
(None, 32)	0
(None, 4)	132
	(None, 30, 32) (None, 26, 250) (None, 250) (None, 64) (None, 64) (None, 64) (None, 32) (None, 32)

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Total params: 378,526 Trainable params: 378,526 Non-trainable params: 0



# **LSTM NN**

```
model_lstm = Sequential([
    Embedding(num_words, 32, input_length=max_news_len),
    SpatialDropout1D(0.2),
    LSTM(16, dropout=0.2, recurrent_dropout=0.2),
    Dense(32, activation='relu'),
    Dropout(0.2),
    Dense(16, activation='relu'),
```

```
Dropout(0.2),
Dense(4, activation='softmax')])
```

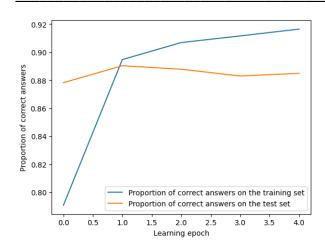
model\_lstm.summary()

Model: "sequential\_10"

Layer (type)	Output Shape	Param #
embedding_11 (Embedding)	(None, 30, 32)	320000
<pre>spatial_dropout1d_5 (Spatia lDropout1D)</pre>	(None, 30, 32)	0
lstm_4 (LSTM)	(None, 16)	3136
dense_19 (Dense)	(None, 32)	544
dropout_3 (Dropout)	(None, 32)	0
dense_20 (Dense)	(None, 16)	528
dropout_4 (Dropout)	(None, 16)	0
dense_21 (Dense)	(None, 4)	68

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Total params: 324,276 Trainable params: 324,276 Non-trainable params: 0



## **GRU NN**

```
model_gru = Sequential([
    Embedding(num_words, 32, input_length=max_news_len),
    SpatialDropout1D(0.2),
    GRU(16, dropout=0.2, recurrent_dropout=0.2),
    Dense(32, activation='relu'),
    Dropout(0.2),
    Dense(16, activation='relu'),
    Dropout(0.2),
    Dense(4, activation='softmax')])
```

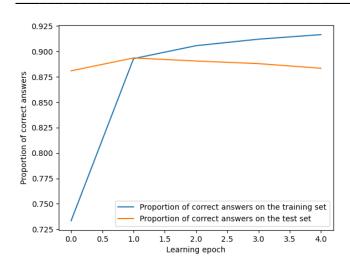
## model\_gru.summary()

Model: "sequential\_11"

Layer (type)	Output Shape	Param #
embedding_12 (Embedding)	(None, 30, 32)	320000
<pre>spatial_dropout1d_6 (Spatia lDropout1D)</pre>	n (None, 30, 32)	0
gru_2 (GRU)	(None, 16)	2400
dense_22 (Dense)	(None, 32)	544
dropout_5 (Dropout)	(None, 32)	0
dense_23 (Dense)	(None, 16)	528
dropout_6 (Dropout)	(None, 16)	0
dense_24 (Dense)	(None, 4)	68

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Total params: 323,540 Trainable params: 323,540 Non-trainable params: 0



Adding more number of layers increased accuracy for train data set more for CNN rather than LSTM and GRU. At some point, number of layers almost didn't change the accuracy for LSTM and GRU models. Also, it caused overfitting on test set for all of them. Even adding dropout layers didn't change the situation much. The current number of layers is one of stable variants of models.

We can use current model in news companies such as The Guardian, The Economist and so on to save human resources and correctly identify news categories and topic. Furthermore, by tweaking the model, we can also use it to look for controversial words and topics to either avoid

publishing news or fixing the language of it. It allows easier censorship and saves time reading whole article and looking for such words.