

# Fine-tuning DistilBERT for South Park character classification

Project in TDDE09

Olle Ulfvin, Tobias Grandin Karanta,  
Philip Gustafsson and Matteo Cutroni



# Content



# Data-Set

- Consisted of [episode | character | line]
- A lot of characters, we chose top 5 characters
- Imbalanced

Character	Number of Lines (Training)	Number of Lines (Evaluation)
Cartman	6120	1530
Stan	3695	924
Kyle	3481	870
Randy	1897	474
Butters	1435	359
Total	16628	4157





# Baseline Model

- DistilBERT as pre-trained model
- Fine-tuned on South Park data-set
- Learning rate 1e-4, Batch size 8, no weight decay

	Macro F1	Accuracy
Baseline	0.504004	0.528506



# CW-Model

- Baseline but with Class Weights
- Introduced to combat class imbalance

	Macro F1	Accuracy
Baseline	0.504004	0.528506
CW	0.499149	0.521289



# HPFT-Model

- Hyperparameter fine-tuning
- Large search for best hyperparameters
- Learning rate 5e-5, Batch size 8 and weight decay 0.1

	Macro F1	Accuracy
Baseline	0.504004	0.528506
CW	0.499149	0.521289
HPFT	0.509452	0.532355



# LLRD-Model

- Layer-wise learning rate decay
- Lower layer => Lower learning rate
- Starting learning rate  $5e-5$  and a decay rate of 0.9.

	Macro F1	Accuracy
Baseline	0.504004	0.528506
CW	0.499149	0.521289
HPFT	0.509452	0.532355
LLRD	0.508115	0.528506



# Classification with Alternating Normalization (CAN)

- Non-parametric post processing technique
- Refines predictions for ambiguous examples
- Normalizes probability distributions
- Proven to improve results for classifiers

Example 1:

Input text: Yeah. Good job, wizard fat ass! Now we're totally lost.

True label: Kyle

Original prediction: Cartman

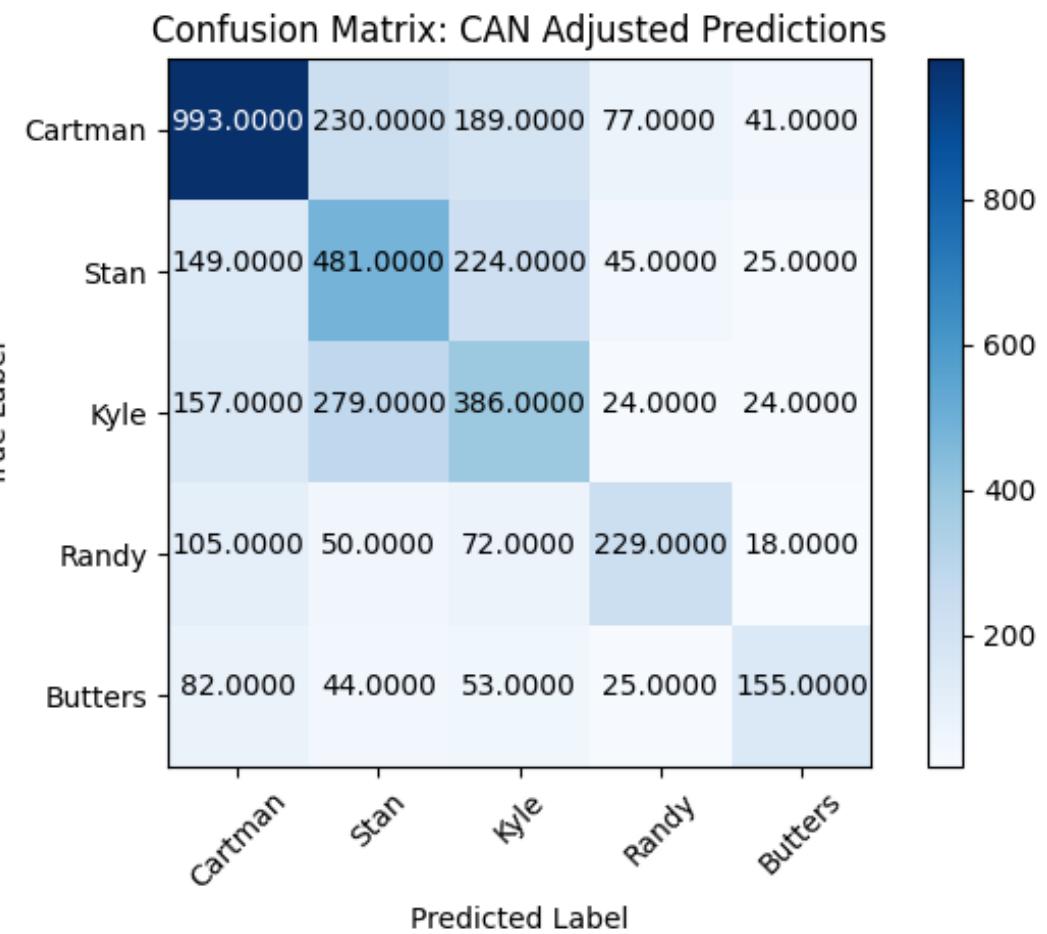
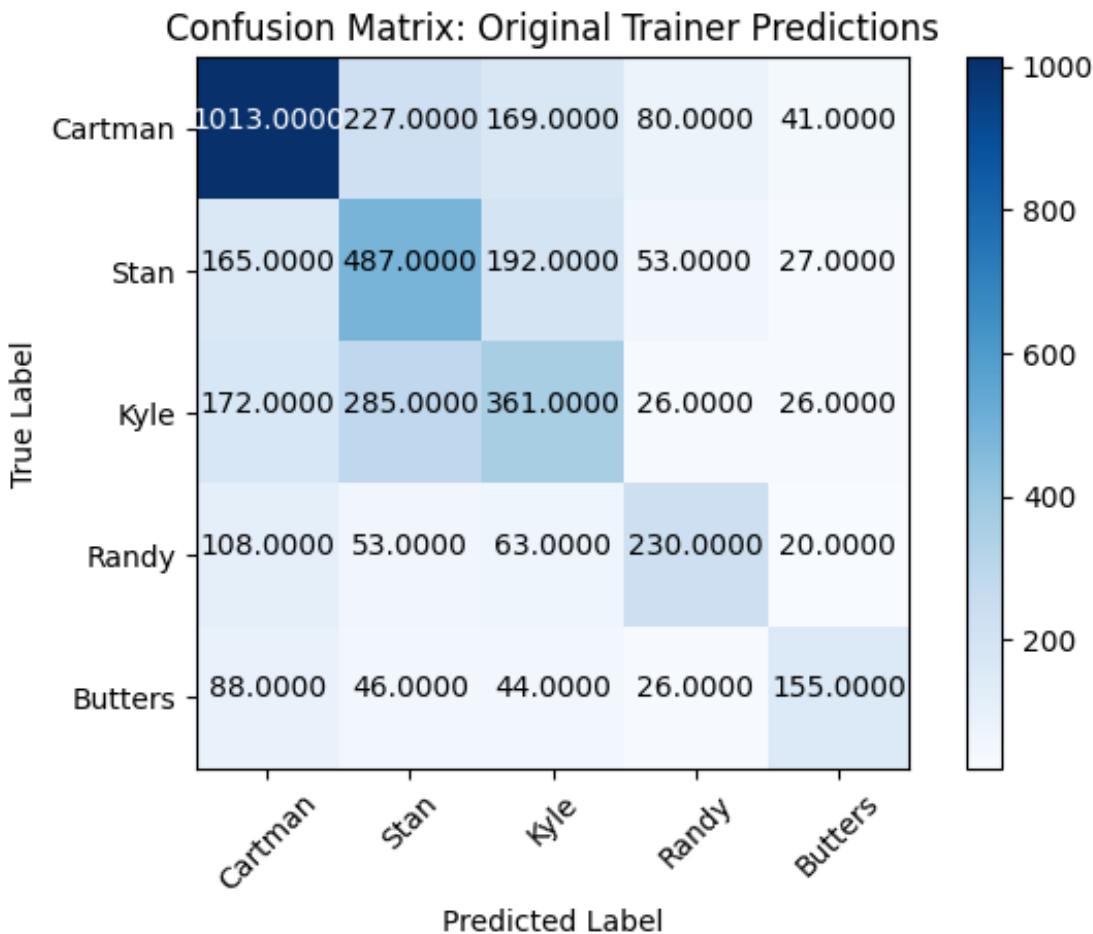
CAN adjusted prediction: Kyle

Original percentages: Cartman: 45.28%, Stan: 13.85%, Kyle: 38.26%, Randy: 0.34%, Butters: 2.27%

CAN adjusted percentages: Cartman: 46.19%, Stan: 0.67%, Kyle: 53.14%, Randy: 0.00%, Butters: 0.00%



# CAN Results



# Results

	<b>Macro F1</b>	<b>Accuracy</b>
Baseline	0.504004	0.528506
CW	0.499149	0.521289
HPFT	0.509452	0.532355
LLRD	0.508115	0.528506

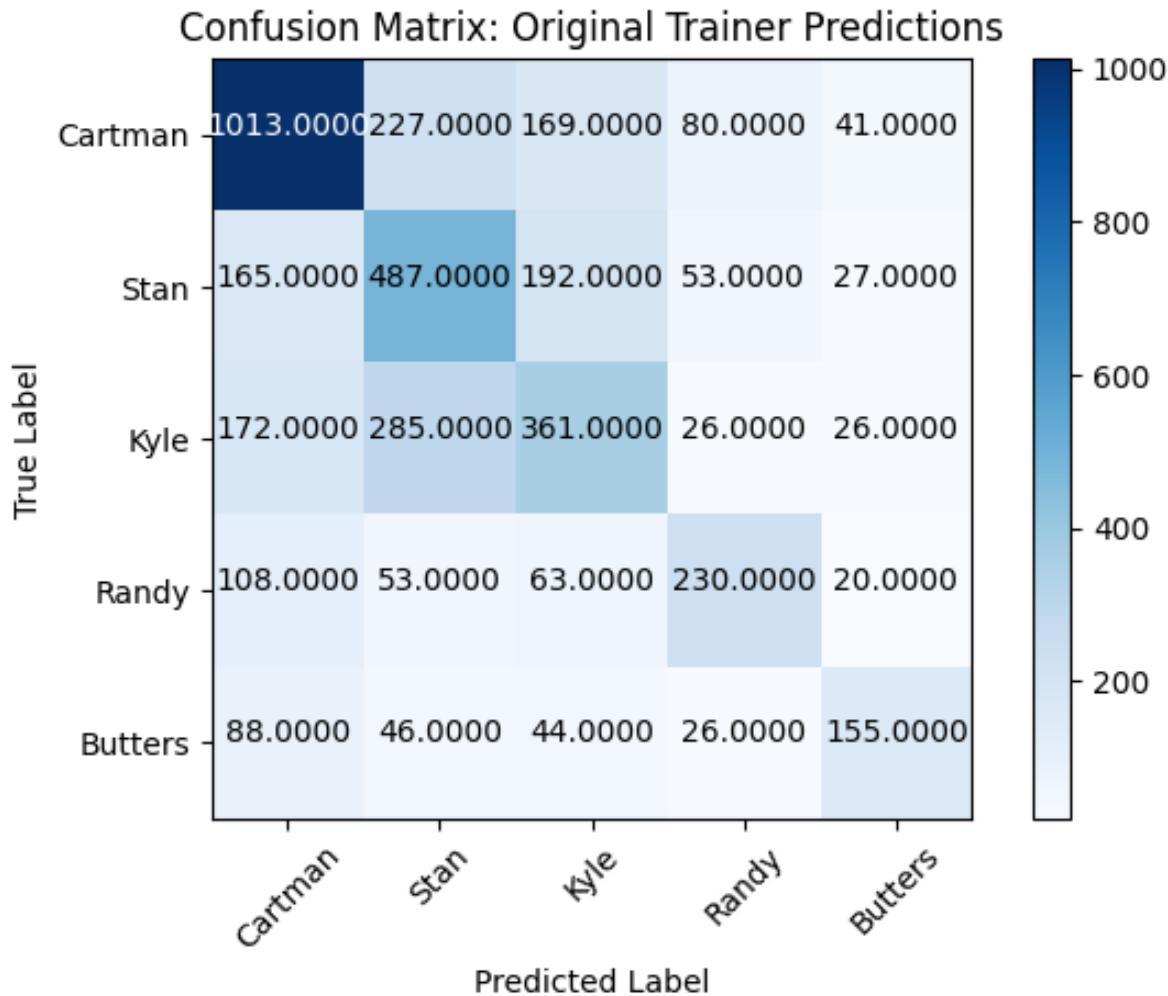
# Why are the results not improving?

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- In more ambiguous cases, it is somewhat uncertain.

Predicted Label	Attribution Label	Word Importance
2 (0.06)	<b>I can't believe what I'm seeing.</b>	[CLS] i can 't believe what i ' m seeing . [SEP]
2 (0.33)	<b>I can't believe what I'm seeing.</b>	[CLS] i can 't believe what i ' m seeing . [SEP]
2 (0.51)	<b>I can't believe what I'm seeing.</b>	[CLS] i can 't believe what i ' m seeing . [SEP]
2 (0.05)	<b>I can't believe what I'm seeing.</b>	[CLS] i can 't believe what i ' m seeing . [SEP]
2 (0.06)	<b>I can't believe what I'm seeing.</b>	[CLS] i can 't believe what i ' m seeing . [SEP]

# Confusion matrix



# What could the model do?

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- Model could connect some words with some characters

Predicted Label	Attribution Label	Word Importance
3 (0.00)	<b>and? your turn, sharon.</b>	[CLS] and ? your turn , sharon . [SEP]
3 (0.00)	<b>and? your turn, sharon.</b>	[CLS] and ? your turn , sharon . [SEP]
3 (0.00)	<b>and? your turn, sharon.</b>	[CLS] and ? your turn , sharon . [SEP]
3 (1.00)	<b>and? your turn, sharon.</b>	[CLS] and ? your turn , sharon . [SEP]
3 (0.00)	<b>and? your turn, sharon.</b>	[CLS] and ? your turn , sharon . [SEP]

# Conclusion (results)

Model can find character-specific patterns, but...

Many sentences does not alone contain enough information to deduce the character who said it (see ambiguous cases).



Questions?