

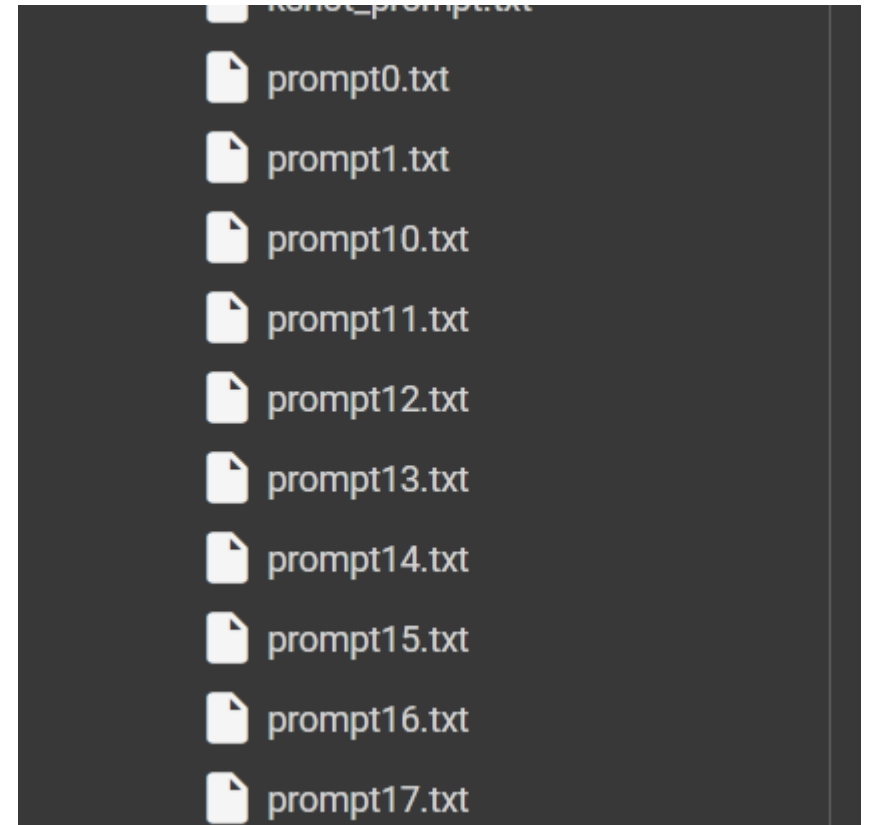
# Symbol Tuning Benchmark

## Symbol tuning

- Change labels to numbers.
- Trying to not mention anything related to 'important' or 'not important' tags in the prompt.

## Symbol tuning

- Cleaned the code.
- Saving each prompt for more analyses.



# Symbol tuning

- *First step:*
  - Change the labels '1's to '58's.
  - Change the labels '0's to '47's.
- We tried to use labels that the model hasn't seen.
- So, it doesn't use its' predefined knowledge to tag news with 'important' or 'not important' tags.

# Symbol tuning

- Surprisingly the Aya LLM tends to generate '58' more than '47' ones.
- This might be because there is more details or definition defined about '58' label.
- Or this might be caused by '58' being the first label.
- Or the dataset being imbalanced!
- The result shown is in 'k=20' mode.

```
test_df_counter is 24
answer of row 24 is 47 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 25
answer of row 25 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 26
answer of row 26 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 27
answer of row 27 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 28
answer of row 28 is 47 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 29
answer of row 29 is 47 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 30
answer of row 30 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
dataframe saved to csv file at iteration 30
test_df_counter is 31
answer of row 31 is 47 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 32
answer of row 32 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 33
answer of row 33 is 47 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 34
answer of row 34 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 35
answer of row 35 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 36
answer of row 36 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 37
answer of row 37 is 47 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 38
answer of row 38 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 39
answer of row 39 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 40
answer of row 40 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
dataframe saved to csv file at iteration 40
test_df_counter is 41
answer of row 41 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 42
answer of row 42 is 47 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 43
answer of row 43 is 47 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 44
answer of row 44 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 45
answer of row 45 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
test_df_counter is 46
answer of row 46 is 58 and k is 20.      Text type: only_title  Real tag: 1.0
test_df_counter is 47
answer of row 47 is 58 and k is 20.      Text type: only_title  Real tag: 0.0
```

# Symbol tuning

- The result shown here is with k=0 shot prompts.
- The model only generates '58' as an answer!
- We can interpret two things from the observation:
  - First the k shot example help the model to obtain knowledge about '47' labels therefore resulting to predict some titles as 'not important' or '47'.
  - Second, we should include in prompt what is 'not important' or '47' label, only including information about what is known as 'important' result in generating only 'important' labels.

```
46 print(f"dataframe saved to csv file at iteration {i}")

... test_df_counter is 0
answer of row 0 is 58 and k is 0.      Text type: only_title  Real tag: 0.0
dataframe saved to csv file at iteration 0
test_df_counter is 1
answer of row 1 is 58 and k is 0.      Text type: only_title  Real tag: 0.0
test_df_counter is 2
answer of row 2 is 58 and k is 0.      Text type: only_title  Real tag: 1.0
test_df_counter is 3
answer of row 3 is 58 and k is 0.      Text type: only_title  Real tag: 1.0
test_df_counter is 4
answer of row 4 is 58 and k is 0.      Text type: only_title  Real tag: 0.0
test_df_counter is 5
answer of row 5 is 58 and k is 0.      Text type: only_title  Real tag: 0.0
test_df_counter is 6
answer of row 6 is 58 and k is 0.      Text type: only_title  Real tag: 0.0
test_df_counter is 7
answer of row 7 is 58 and k is 0.      Text type: only_title  Real tag: 0.0
test_df_counter is 8
answer of row 8 is 58 and k is 0.      Text type: only_title  Real tag: 0.0
test_df_counter is 9
answer of row 9 is 58 and k is 0.      Text type: only_title  Real tag: 0.0
test_df_counter is 10
answer of row 10 is 58 and k is 0.     Text type: only_title  Real tag: 1.0
dataframe saved to csv file at iteration 10
test_df_counter is 11
answer of row 11 is 58 and k is 0.     Text type: only_title  Real tag: 0.0
test_df_counter is 12
answer of row 12 is 58 and k is 0.     Text type: only_title  Real tag: 0.0
test_df_counter is 13
answer of row 13 is 58 and k is 0.     Text type: only_title  Real tag: 0.0
test_df_counter is 14
answer of row 14 is 58 and k is 0.     Text type: only_title  Real tag: 0.0
test_df_counter is 15
```

# Symbol tuning

- The result shown here is with k=1 shot prompts.
- The model generates '47' labels sporadically.
- This means that one example provided in the prompt was not enough to give the model enough information to predict more labels as '47'.
- But it shows that even providing one example can change the output!

```
answer of row 0 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
dataframe saved to csv file at iteration 0
test_df_counter is 1
answer of row 1 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 2
answer of row 2 is 58 and k is 1.      Text type: only_title  Real tag: 1.0
test_df_counter is 3
answer of row 3 is 58 and k is 1.      Text type: only_title  Real tag: 1.0
test_df_counter is 4
answer of row 4 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 5
answer of row 5 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 6
answer of row 6 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 7
answer of row 7 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 8
answer of row 8 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 9
answer of row 9 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 10
answer of row 10 is 47 and k is 1.      Text type: only_title  Real tag: 1.0
dataframe saved to csv file at iteration 10
test_df_counter is 11
answer of row 11 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 12
answer of row 12 is 58 and k is 1.      Text type: only_title  Real tag: 0.0
test_df_counter is 13
```

# Symbol tuning

- The result shown here is with k=50 shot prompts.
- The model generates more '47' labels.
- The results shows that the information and details about the 'not important' news is a necessity to override LLM predefined knowledge.

```
test_df_counter is 19
answer of row 19 is 47 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 20
answer of row 20 is 47 and k is 50.      Text type: only_title  Real tag: 0.0
dataframe saved to csv file at iteration 20
test_df_counter is 21
answer of row 21 is 58 and k is 50.      Text type: only_title  Real tag: 1.0
test_df_counter is 22
answer of row 22 is 47 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 23
answer of row 23 is 58 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 24
answer of row 24 is 47 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 25
answer of row 25 is 58 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 26
answer of row 26 is 58 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 27
answer of row 27 is 58 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 28
answer of row 28 is 58 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 29
answer of row 29 is 47 and k is 50.      Text type: only_title  Real tag: 0.0
test_df_counter is 30
answer of row 30 is 58 and k is 50.      Text type: only_title  Real tag: 0.0
dataframe saved to csv file at iteration 30
```



## Symbol tuning

- The challenge to make predictions more accurate is to include clear definition and details for both 'important' and 'not important' news.
- This causes the language model to rely more on the information given in the prompt (or, as we know, in-context learning) rather than on its prior knowledge.

## Symbol tuning results

- Results for  $k = 0$  shot learning:

K = 0	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	17%	14%	93%	24%	96	5

- The shown results is for first 101 entities in test data.

## Symbol tuning results

- Results for  $k = 1$  shot learning:

K = 1	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	48%	19%	86%	31%	63	38

- The shown results is for first 101 entities in test data.

## Symbol tuning results

- Results for  $k = 5$  shot learning:

K = 5	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	47%	16%	64%	25%	58	43

- The shown results is for first 101 entities in test data.

## Symbol tuning results

- Results for  $k = 20$  shot learning:

K = 20	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	49%	15%	57%	24%	54	47

- The shown results is for first 101 entities in test data.

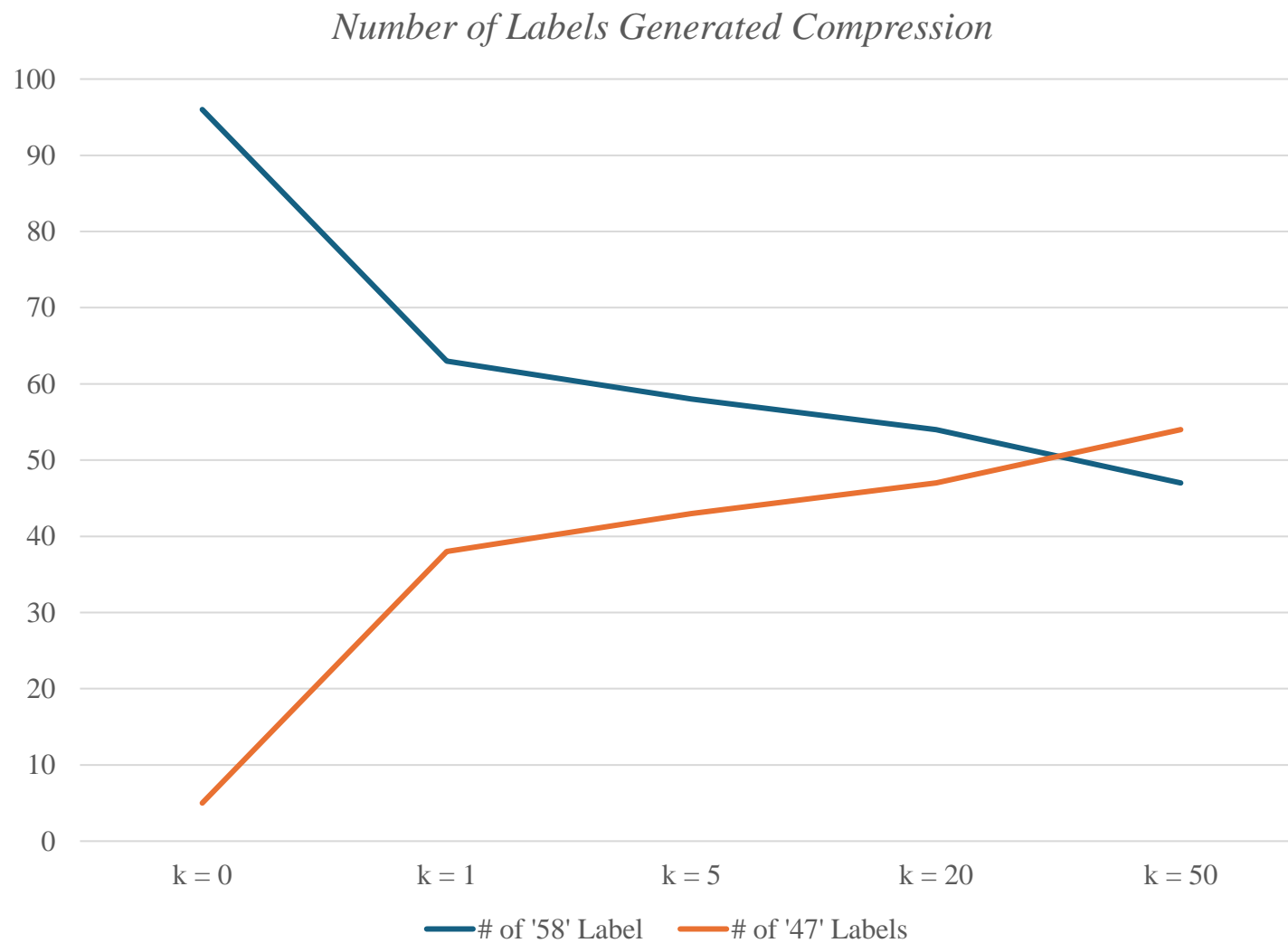
## Symbol tuning results

- Results for k = 50 shot learning:

K = 50	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	55%	17%	57%	26%	47	54

- The shown results is for first 101 entities in test data.

# Symbol tuning results



# Symbol tuning feasible improvements

- Possible future improvements:
  - Change the prompt: The problem observed here is that the prompt lacks a definition for 'important' news but details and definitions for 'not important' ones.
  - Changing the 'important' label to something that is harder to generate because our dataset is imbalanced, and we have little 'important' news compared to 'not important' ones. Therefore, it is logical to make the 'important' label harder to generate for the LLM model.
  - Including in the prompt that we have way less 'important' news than 'not important' ones; therefore, the model should be more sensitive and conservative in generating the 'important' label.
  - Including the chain of thoughts context with the examples provided in the prompt to make the decision for the model more logical and with more reasoning information.



## Symbol tuning results

- Here, we analyze the results achieved from the first 400 indices from our test dataset.
  - The number of total '1' labels is 77, and for '0' labels is 323.

# of '1' labels	# of '0' labels
77	323

## Symbol tuning results

- Results for  $k = 0$  shot learning:

K = 0	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	21%	19%	97%	32%	387	13

- The shown results is for first 400 entities in test data.
- The high percentage achieved by the model in recall metrics is due to mostly predicting '58' labels.

## Symbol tuning results

- Results for  $k = 1$  shot learning:

K = 1	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	53%	24%	69%	36%	218	182

- The shown results is for first 400 entities in test data.

## Symbol tuning results

- Results for k = 5 shot learning:

K = 5	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	49%	24%	78%	37%	249	151

- The shown results is for first 400 entities in test data.
- Highest f1-score reached!

## Symbol tuning results

- Results for k = 20 shot learning:

K = 20	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	48%	23%	71%	34%	242	158

- The shown results is for first 400 entities in test data.

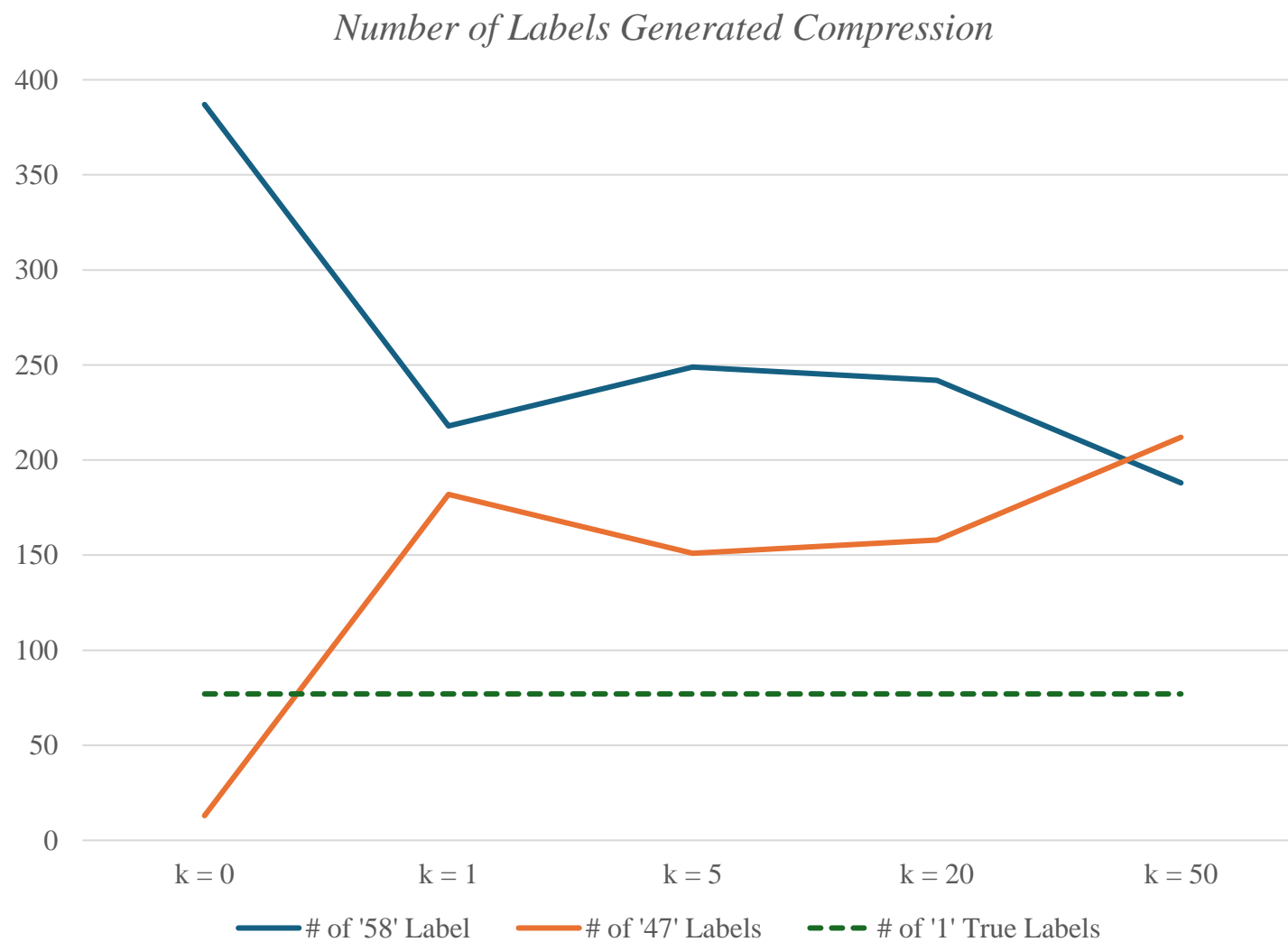
## Symbol tuning results

- Results for k = 50 shot learning:

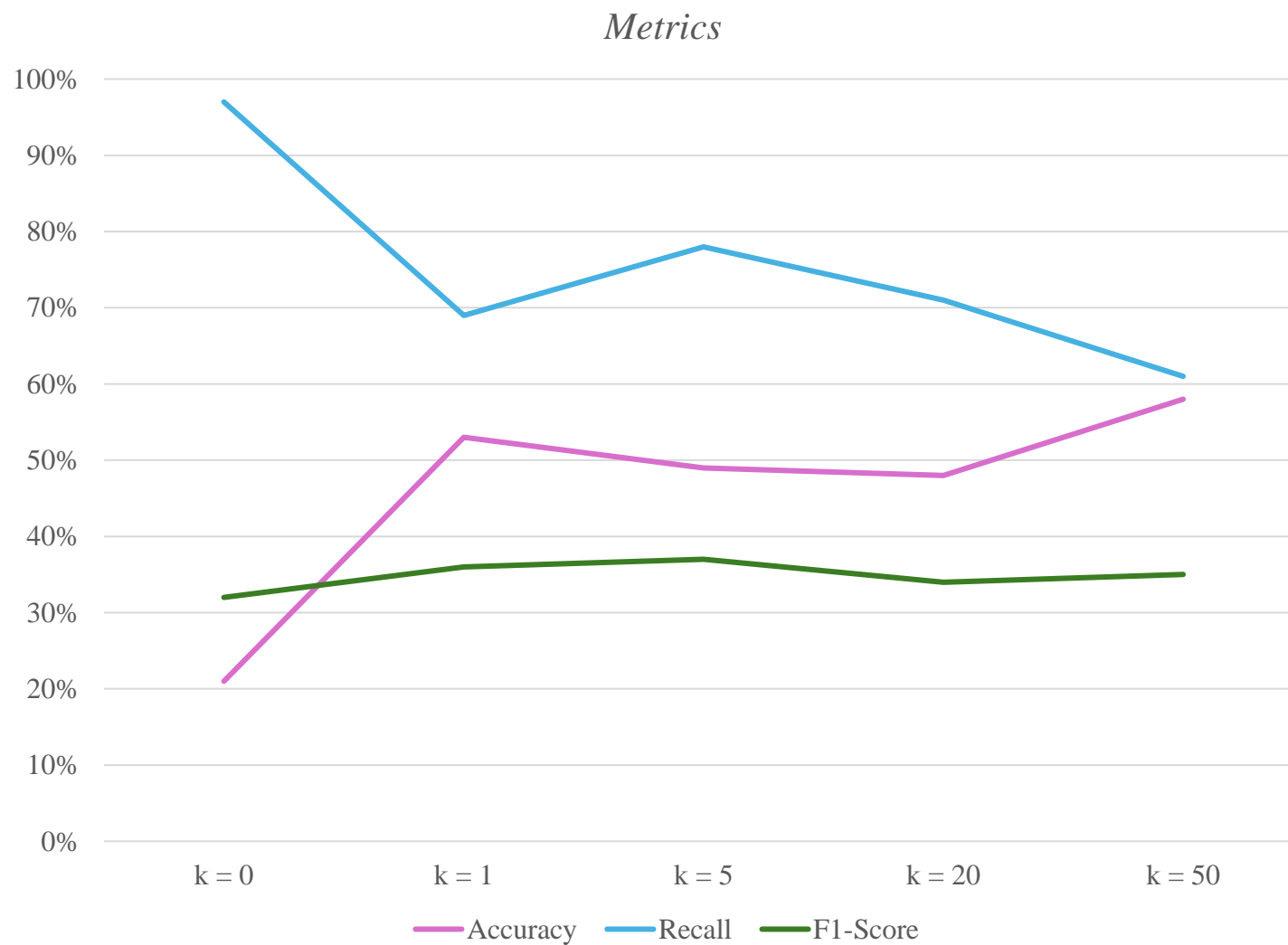
K = 50	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
Title	57%	25%	61%	35%	188	212

- The shown results is for first 400 entities in test data.
- Highest number of '47' predicted!

# Symbol tuning results



# Symbol tuning results





## Symbol tuning results

- Now, we analyze the whole data in test dataset.
  - The total number of labeled news is '1179'
  - The number of total '1' labels is 196, and for '0' labels is 983.

# of '1' labels	# of '0' labels
196	983

## Symbol tuning results

- Results for  $k = 0$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 0$	19%	17%	97%	28%	1121	40

## Symbol tuning results

- Results for  $k = 1$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 1$	53%	21%	67%	32%	609	552

## Symbol tuning results

- Results for  $k = 5$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 5$	49%	21%	77%	33%	701	460

## Symbol tuning results

- Results for  $k = 20$  shot learning:

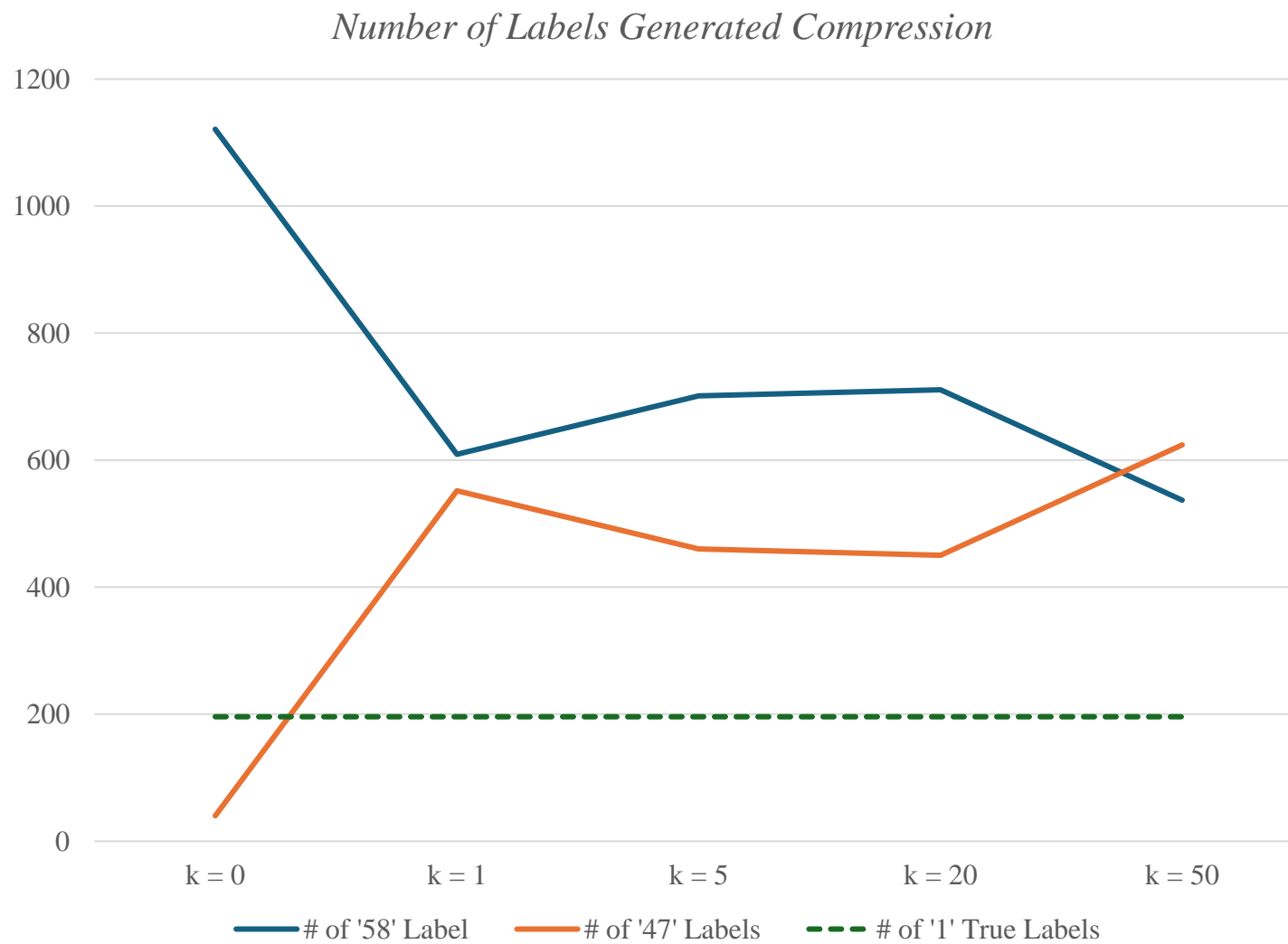
Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 20$	46%	20%	73%	31%	711	450

## Symbol tuning results

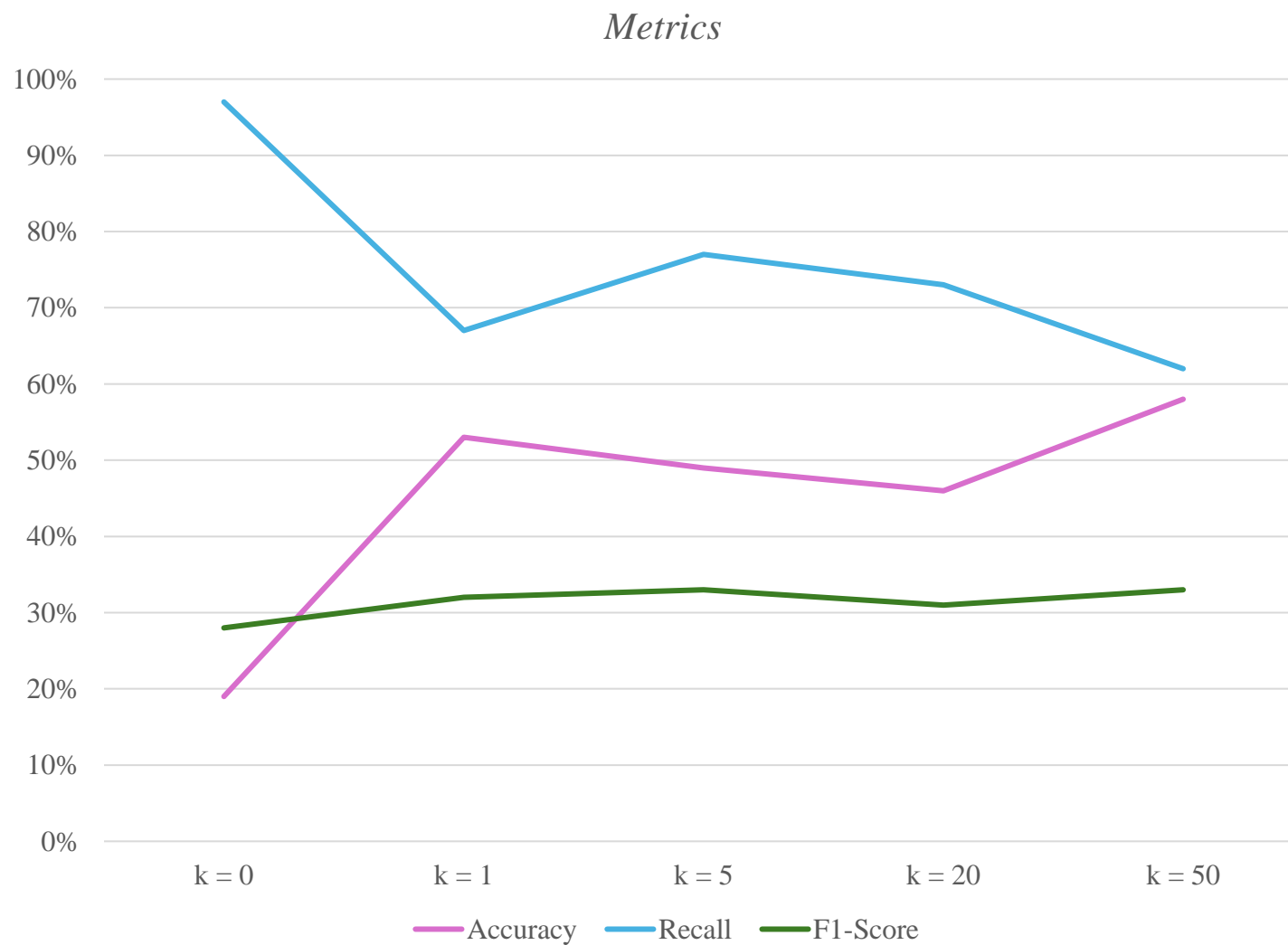
- Results for  $k = 50$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 50$	58%	22%	62%	33%	537	624

# Symbol tuning results



# Symbol tuning results





## Symbol tuning results

- All the results is shown here:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
k = 0	19%	17%	97%	28%	1121	40
k = 1	53%	21%	67%	32%	609	552
k = 5	49%	21%	77%	33%	701	460
k = 20	46%	20%	73%	31%	711	450
k = 50	58%	22%	62%	33%	537	624
Tr Labels					196	983

## Symbol tuning results

- And this is the result for first 400 data in our test data:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
k = 0	21%	19%	97%	32%	387	13
k = 1	53%	24%	69%	36%	218	182
k = 5	49%	24%	78%	37%	249	151
k = 20	48%	23%	71%	34%	242	158
k = 50	57%	25%	61%	35%	188	212
Tr Labels					77	323

- This suggest that we can rely on the results achieved from first 400 samples.
  - As it can be interpreted that there is little difference between results from all samples and n=400 samples.

## Symbol tuning prompt

- Now we analyze the changes made to the prompt.
- The first change is adding information and details about ‘not important’ news.
- The results can be seen in following slides.

## Symbol tuning results

- As same as before we have 77 'important' labels and 324 'not important' labels in our first 401 samples from test data.

# of '1' labels	# of '0' labels
77	324

## Symbol tuning results

- Results for  $k = 0$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 0$	27%	20%	95%	33%	363	38

- By adding a definition for 'not important' news we observe an increase in detecting '47' labels.
- This results in more accuracy and f1-score!

## Symbol tuning results

- Results for  $k = 1$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 1$	41%	23%	86%	36%	293	108

- The accuracy dropped here!
- This is because the model is less sensitive to the example provided in prompt. As we can understand the increase in number of '47' labels predicted is steadier, revealing that the model is acting more nuanced about the example provided.

## Symbol tuning results

- Results for  $k = 5$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 5$	46%	22%	71%	34%	249	152

- Here we saw a small increase to the number of '47' labels predicted.
- This means the model shows more resistance to the examples because of the change in prompt.

## Symbol tuning results

- Results for  $k = 20$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 20$	58%	26%	69%	38%	202	199

- Highest accuracy and f1-score achieved so far!



## Symbol tuning results

- Results for  $k = 50$  shot learning:

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
$k = 50$	57%	24%	56%	33%	180	221

- With many examples provided eventually the model predicted more '47' labels than '58' ones.

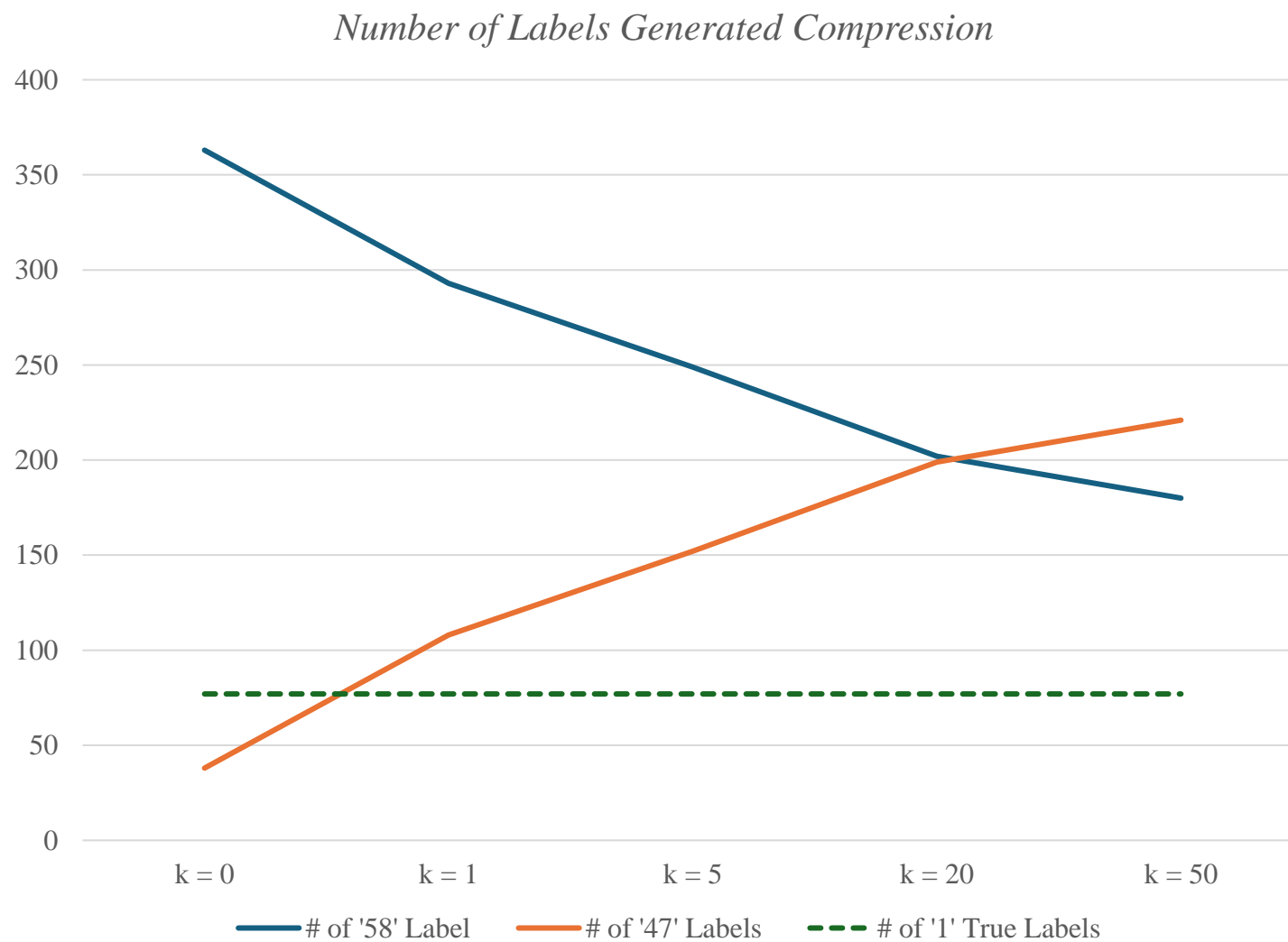
## Symbol tuning results

- The whole results can be seen here:

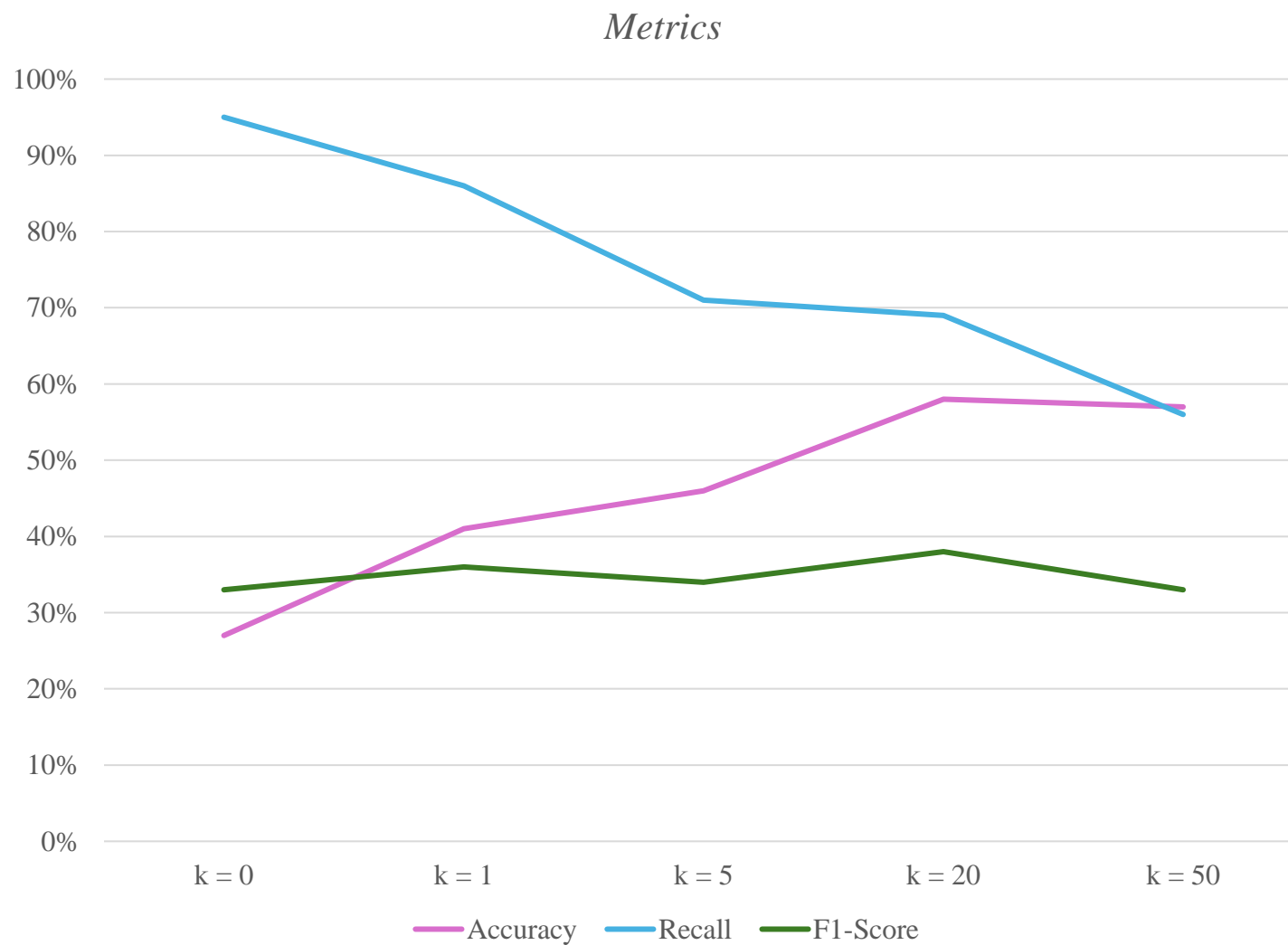
Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
k = 0	27%	20%	95%	33%	363	38
k = 1	41%	23%	86%	36%	293	108
k = 5	46%	22%	71%	34%	249	152
k = 20	58%	26%	69%	38%	202	199
k = 50	57%	24%	56%	33%	180	221
Tr Labels					77	323

- The accuracy and f1-score in k = 20 scenario saw the biggest increase.

# Symbol tuning results



# Symbol tuning results



## Symbol tuning

- The results illustrate that even a small change in prompt can have dramatic alter the results and be observed in symbol tuning.

## Symbol Tuning Gemma-7b-it

- Now we tested Gemma-7b-it model with the version 2 prompt and the results is illustrated in the following slides.
- One thing to note is that this model doesn't response to our prompt with just one label of '47' or '58', instead it responded with a sentence to explain why it is detecting what label.
  - For this reason, we just extract the first number from response and save it as the final result.

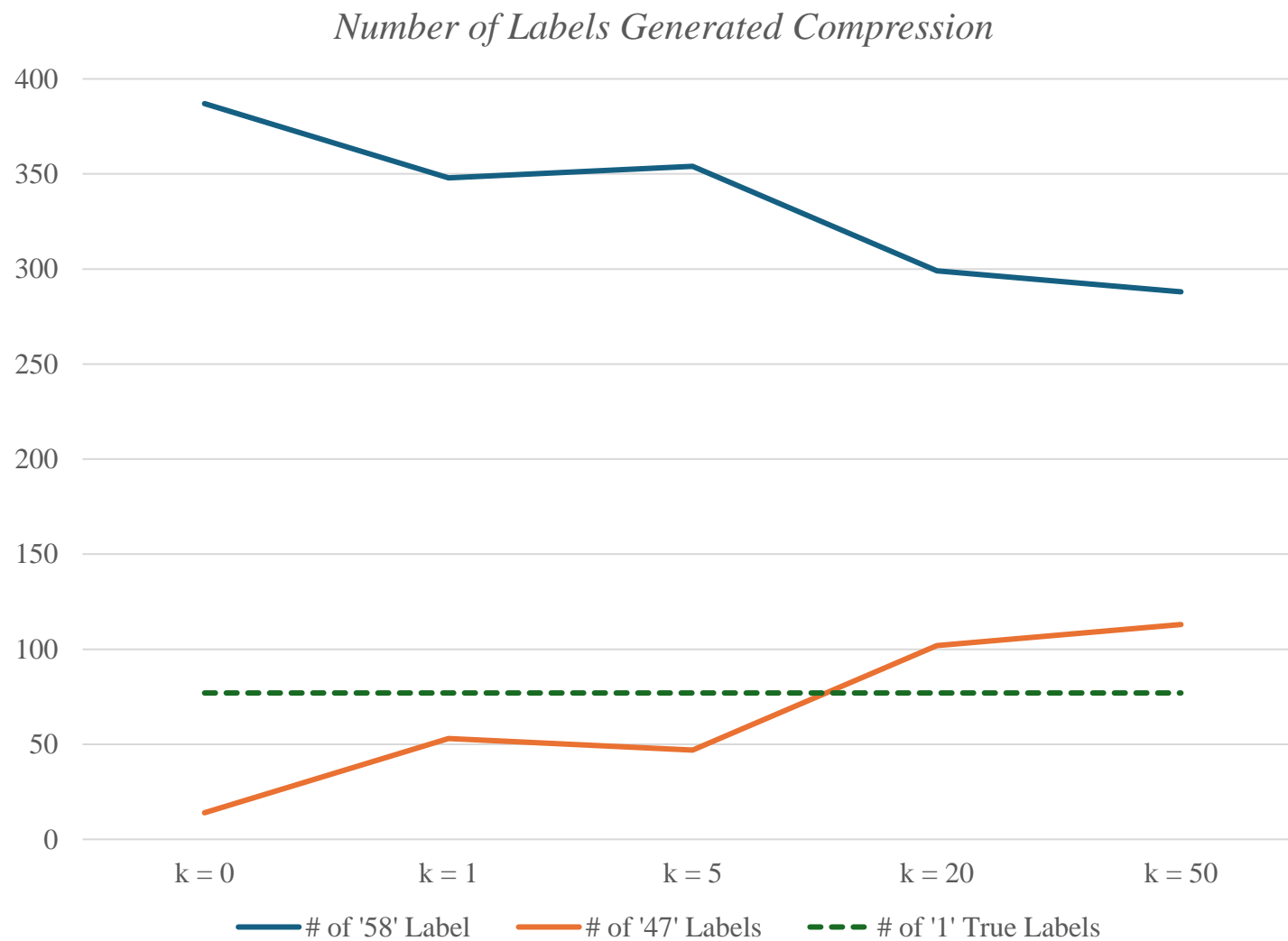
## Symbol Tuning Gemma-7b-it Results

- The whole results can be seen here:
  - This is the result for first 401 samples of test dataset.

Title Only	Accuracy	Precision	Recall	F1-Score	# of '58'	# of '47'
k = 0	23%	20%	100%	33%	387	14
k = 1	29%	20%	91%	33%	348	53
k = 5	29%	21%	95%	34%	354	47
k = 20	39%	22%	86%	35%	299	102
k = 50	40%	22%	81%	34%	288	133
Tr Labels					77	323

- We can interpret a loss in accuracy compared to Aya model.

# Symbol Tuning Gemma-7b-it Results





# Symbol Tuning Gemma-7b-it Results



## Symbol Tuning Gemma-7b-it

- As it can be seen there is a direct correlation between the numbers of labels generated to the classification metrics.
  - Therefore, it is becoming an important agenda to design the prompt in a way for having more '47' or 'not important' labels in response.
- One of the reasons that in  $k = 50$  we observe the increase in 'not important' labels generated is the concept of 'forgetting'. When the model receives too much information in prompt it forgets the main points and that ought to return '47' as the response.

## Symbol Tuning Gemma-7b-it

- Result 321,  $k = 1$ :

**\*\*خروجی: 58\*\***

متن بالا از نوع 58 است، زیرا برای یک audience فارسی زبان با importance بالایی دارد و شامل خبرهای مهم و اطلاعاتی برای یک audience فارسی زبان است.

- Result 321,  $k = 5$ :

**\*\*خروجی: 58\*\***

متن بالا از نوع 58 است، زیرا برای بیشتر کاربران فارسی زبان اهمیت بالایی دارد و به عبارت دیگر، جمعیت زیاد و بزرگی از ایرانیان مایل هستند که آن متن را بخوانند و یا برای یکدیگر بفرستند.

## Symbol Tuning Gemma-7b-it

- Result 321, k = 20:

**\*\*خروجی: 47\*\***  
متن بالا از نوع 47 است، زیرا که برای یک بخش خاص و کوچکی از جامعه نوشته شده است و گسترده‌ی وسیعی از جامعه را درگیر نکند.

- Result 321, k = 50:

**\*\*خروجی: 58\*\***  
متن بالا از نوع 58 است، زیرا برای بیش‌تر کاربران فارسی‌زبان اهمیت بالایی دارد و شامل خبرهای با موضوع‌های گوناگون **gunaan** است.

## Symbol Tuning Gemma-7b-it

- Result 381,  $k = 1$ :

**\*\*خروجی: 58**

متن بالا از نوع 58 است، زیرا برای بیشتر کاربران فارسی زبان importance بالایی دارد و شامل خبرهای مهم و kvuli Readability بالا است.

- Result 381,  $k = 5$ :

**\*\*خروجی: 58**

متن بالا از نوع 58 است، زیرا برای بیشتر کاربران فارسی زبان اهمیت بالایی دارد و شامل خبرهای که برای یک جامعه بزرگ و پرازد ایرانیان مهم است.

## Symbol Tuning Gemma-7b-it

- Result 381, k = 20:

The text is about the reactions of Iranian users to a recent event. The text is about the reactions of Iranian users to a recent event. It is a type 58 text because it is relevant to a large audience of Iranian people and is likely to be read by many people

- Result 381, k = 50:

Answer: 47

متن بالا از نوع 47 است، زیرا با یک 主题 خاص و کوچکی از جامعه سروکار دارد.

## Symbol Tuning Gemma-7b-it Prompt

- Result 261, k = 1:

متن نمونه: جاماندگان سهام عدالت بخوانند | اعطای سهام عدالت به این افراد در چه مرحله‌ای است؟ خروجی: 47

از روی نمونه‌های بالایی یاد بگیر و خروجی را مشخص کن (فقط 58 یا 47).  
حال با توجه به «نمونه‌های بالا»، برای متن زیر تنها در یک واژه پاسخ بده که با توجه به مفاهیمی که در بالا مطرح شد و قدرت استنتاجی که خودت داری، آیا متن 58 حساب می‌شود یا 47. (58 یا 47):

جاماندگان سهام عدالت بخوانند | تکلیف ۳,۵ میلیون جامانده از سهام عدالت چه می‌شود؟

## Symbol Tuning Gemma-7b-it Prompt

- Result 261, k = 5:

.نمونه‌ها: چند نمونه پایین را ببین و باتوجه به آن‌ها به سوال پایین پاسخ بده

متن نمونه: جاماندگان سهام عدالت بخوانند | اعطای سهام عدالت به این افراد در چه مرحله‌ای است؟ خروجی: 47

متن نمونه: متقاضیان فروش سهام عدالت بخوانند خروجی: 58

متن نمونه: خبر مهم درباره سهام عدالت/ جزئیات تازه درباره سهام عدالت جدید خروجی: 58

متن نمونه: ۱۰ میلیون تومان برای جاماندگان سهام عدالت خروجی: 58

متن نمونه: تکلیف مانده سود سهام عدالت چه شد؟ خروجی: 58



# Symbol Tuning Gemma-7b-it Prompt

- Result 261,  
k = 20:

متن نمونه: جاماندگان سهام عدالت بخوانند | اعطای سهام عدالت به این افراد در چه مرحله‌ای است؟ خروجی: 47

متن نمونه: متقاضیان فروش سهام عدالت بخوانند خروجی: 58

متن نمونه: خبر مهم درباره سهام عدالت/ جزییات تازه درباره سهام عدالت جدید خروجی: 58

متن نمونه: ۱۰ میلیون تومان برای جاماندگان سهام عدالت خروجی: 58

متن نمونه: تکلیف مانده سود سهام عدالت چه شد؟ خروجی: 58

متن نمونه: ارزش سهام عدالت امروز ۵ بهمن ۱۴۰۰ خروجی: 47

متن نمونه: ارزش سهام عدالت امروز ۴ بهمن ۱۴۰۰ خروجی: 47

متن نمونه: واریز سود سهام عدالت منتفی شد؟! خروجی: 58

متن نمونه: ارزش سهام عدالت امروز ۳۰ بهمن ۱۴۰۰ خروجی: 47

متن نمونه: ارزش سهام عدالت امروز ۲۹ دی ۱۴۰۰ خروجی: 47

متن نمونه: آزاد شدن فروش سهام عدالت شاید وقتی دیگر خروجی: 58

## Symbol Tuning Gemma-7b-it Prompt

- Result 261,  
k = 20:

متن نمونه: وعده جدید رییس سازمان بورس برای سهامداران/ جزییات پرداخت سود سهام عدالت خروجی: 58

متن نمونه: زمان واریز سود سهام عدالت مشخص شد ؛ سهامداران منتظر باشند | مبلغ سود چقدر است؟ خروجی: 58

متن نمونه: اعلام زمان نهایی واریز سود سهام عدالت | مبلغ واریزی چقدر خواهد بود ؟ خروجی: 58

متن نمونه: سود سهام عدالت آذر ۱۴۰۱؛ جزییات دقیق رقم واریزی و شیوه محاسبه سود خروجی: 58

طعنه اولیانوف به بورل: زیان تهدید درباره ایران جواب نمی دهد / واکنش رئیس سازمان خصوصی سازی به حاشیه جدید فروش مدارس خیرساز خروجی: 47

متن نمونه: ثبت نام اینترنتی افراد بیکار تحت پوشش بهزیستی همدان آغاز شد خروجی: 47

متن نمونه: کدام خدمات دندانپزشکی تحت پوشش بیمه است؟ خروجی: 58

متن نمونه: صداقت یا عدالت؟ خروجی: 47

متن نمونه: اروپا و مساله ایران/بازار سهام می تواند به آینده خوشبین باشد؟/لغت سازی و مصوبه مولدسازی خروجی: 47

## Symbol Tuning Gemma-7b-it

- Result 261,  $k = 1$ :

**\*\*خروجی: 47\*\***  
متن بالا از نوع 47 است، زیرا با یک گروه خاص از Users ارتباط دارد و به یک موضوع خاص محدود است.

- Result 261,  $k = 5$ :

**\*\*خروجی: 58\*\***  
متن بالا از نوع 58 است، زیرا برای بیشتر کاربران فارسی زبان importance بالایی دارد و شامل خبرهای مهم و با خبرهای محلی یا تخصصی که برای یک قشر کوچک یا جامعه خاصی از کاربران باشد.

## Symbol Tuning Gemma-7b-it

- Result 261, k = 20:

متن بالا از نوع 47 است، زیرا که مربوط به یک بخش خاص و کوچکی از جامعه است، به saber، جاماندگان سهام عدالت. \*\*خروجی: 47\*\*

- Result 261, k = 50:

متن بالا از نوع 47 است، زیرا با یک 主题 خاص و کوچکی از جامعه سروکار دارد. \*\*خروجی: 47\*\*

## Symbol Tuning Gemma-7b-it

- It seems that the reasoning is inconsistent across different k shot learning prompts.
  - The model is very sensitive to the example provided, especially in k=1 situation.
- We see that a mix of English and Persian words is generated in response.
- There is a theory that these small LLM models (parameters < 9b) are having better performance in reasoning task in English compared to Persian.
  - As it seen in one of results, the model tried to provide reason in English language, while the whole prompt is in Persian.
- It is worth experiencing with having instructions in English language and the examples and target text in Persian.

## System-User Prompt Design

- One way to increase the performance of the model is to use System-User Prompt structure.
- In this way, the system prompt is constructed around defining the task and what model should generate.
- The user prompt is considered as the prompt given by the user.
- The system prompt is mostly unchanged throughout the iterations and user prompt is always dynamic.

## System-User Prompt Design

- The input prompt which is only in Persian language:

به عنوان یک درمانگر، شما باید به کاربرانی که از شما سوال می پرسند، مشاوره بدهید و سعی کنید که آن ها را در مورد خودشان احساس بهتری پیدا کنند.  
من حالم خوب نیست، اخیرا یک تصادف بد با ماشین را تجربه کردم، چکار می توانم انجام دهم؟

- Without the use of any system-user prompt instruction.

# System-User Prompt Design

- And this is the result form Gemma2 9b it:

متاسفم که از تصادف بد ماشین رنج می‌بری. این اتفاقات بسیار وحشتناک و تکان‌دهنده هستند.

درک می‌کنم که حال تو خوب نیست و طبیعی است که بعد از چنین تجربه دردناکی احساسات مختلفی مثل غم، ترس، خشم یا گیجی داشته باشی.

چند نکته وجود داره که ممکنه کمکت کنن:

- \* \* \* به خودت زمان بده: \* \* \* درد و غم بعد از تصادف طبیعی است. به خودت زمان بده تا با این احساسات کنار بیایی و به حالت عادی برگردی.
- \* \* \* از کسی کمک بگیر: \* \* \* با دوستان و خانواده‌ات در مورد اتفاقی که افتاده صحبت کن. آنها می‌توانند حمایت و محبت لازم را به تو بدهند.
- \* \* \* به یک درمانگر مراجعه کن: \* \* \* اگر احساسات تو مدام بدتر می‌شوند یا نمی‌توانی با آنها کنار بیایی، به یک روانشناس یا درمانگر مراجعه کن. آنها می‌توانند به تو کمک کنند تا با این تجربه کنار بیایی و به حالت عادی برگردی.
- \* \* \* به خود مراقبت کن: \* \* \* خواب کافی بگیری، غذاهای سالم بخور و ورزش منظم انجام بده. این کارها به بهبود روحیه و جسمی تو کمک می‌کنند.
- \* \* \* از تجربیات مشابه دیگران یاد بگیر: \* \* \* در اینترنت و کتاب‌ها می‌توانید داستان‌های افرادی را پیدا کنید که از تصادف بد ماشین رنج برده‌اند و چگونه با آن کنار آمده‌اند.

فراموش نکن، تو تنها نیستی و این اتفاقات برای همه ممکن است بیفتد. با کمک و مراقبت، می‌توانی از این تجربه عبور کنی و به زندگی عادی خود بازگردی.

- Which is quite acceptable



## System-User Prompt Design

- Now we changed the input prompt to have system-user instruction.

System Prompt: As a therapist you should make advises to users who asks you questions and try to make them feel better about their selves

User Prompt: من حالم خوب نیست، اخیرا یک تصادف بد با ماشین را تجربه کردم، چکار می توانم انجام دهم؟

- In a way that System prompt being in English language and the user prompt being in Persian language.
  - This is due to the reason that the model can understand instructions better in English language and have a better reasoning in that situation.

# System-User Prompt Design

- This the result form Gemma2 9b it for changed prompt:

من متوجه میشم که حالت خوب نیست و تصادف ماشین برایت خیلی سخت بوده. واقعا جای تاسف داره که این اتفاق افتاده.

اول از همه، باید به خودت بگو که این اتفاق برای همه میتونه بیوفته و تو تنها نیستی. خیلی ها بعد از تصادف با مشکلاتی روبرو میشن و نیاز به کمک دارن.

چند تا چیز هست که میتونی انجام بدی:

**\*\* به خودت زمان بده:** بعد از تصادف، طبیعی هست که احساسات مختلفی مثل غم، ترس، خشم و حتی شرمندگی داشته باشی. به خودت زمان بده تا این احساسات رو پردازش کنی و باهاشون کنار بیای.

**\*\* با کسی در موردش صحبت کن:** با کسی که بهش اعتماد داری، مثل دوست، خانواده یا یک مشاور، در مورد اتفاقی که افتاده صحبت کن.

**\*\* به بدن خودت توجه کن:** ممکنه بعد از تصادف، درد یا مشکلاتی در بدنت وجود داشته باشه. حتما به پزشک مراجعه کن و درمان لازم رو انجام بده.

**\*\* به آرامش خودت کمک کن:** با انجام کارهایی که بهت آرامش میده، مثل یوگا، مدیتیشن، یا گوش دادن به موسیقی، به آرامش خودت کمک کن.

**\*\* از منابع کمک موجود استفاده کن:** در ایران، سازمان های مختلفی وجود دارن که به افرادی که در تصادف آسیب دیده اند، کمک میکنند.

**\*\* به یاد داشته باش:** این اتفاق فقط یه قسمت از زندگی تو هست و تو میتونی از پسش بر بیای.

اگر احساس می کنی که با این شرایط کنار نمیایی، حتما به یک مشاور یا روانشناس مراجعه کن.

- Not only the reference time was 2x faster, but also the results became more natural and enhanced.

## System-User Prompt Design

- As the result of the little experience conducted, it is worthwhile to test the system-user prompt design with system prompt being in English (including the k-shot examples in Farsi) and the user prompt being the same.
- In that case it is feasible to not repeat the instructions due to the better understanding of the model.