

Do Large Language Models Extrapolate Personas from Dialogue Context?



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Master's Thesis Defense

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Roadmap

Motivation

Research questions

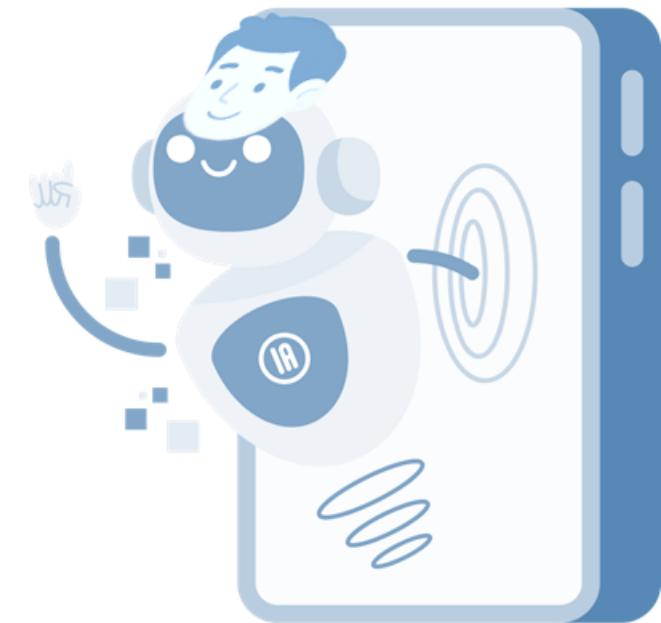
Experimental design

Key findings

Limitations & Future Work

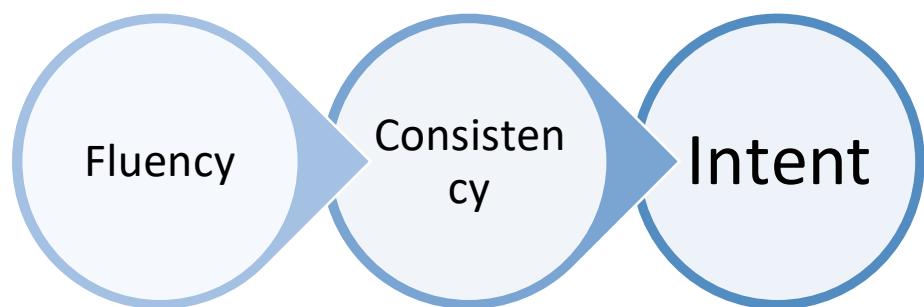
Conclusion

Q&A



Persona Mimicry

A **persona** is the *consistent style, tone, and communicative intent* through which a speaker reveals their identity, expressed in *patterns of word choice, affect, rhetorical strategies, and decision-making cues*.



- Customer service
- Education
- Mental health
- General human-computer interaction:

Persona consistency enhances trustworthiness and satisfaction.

Research Questions

RQ1: is it possible to predict a persona's decision from prior turns only?

RQ2: how much context does it take?

RQ3: can LLMs generate the next utterances aligned with persona's actions?

Study Design – Two complementary experiments

Experiment I

Prediction of binary decisions
in donation to the charity fund
and the amount of money in
the persuasive dialogues

Experiment II

Next-turn generation in travel
domain dialogues, and then
automatic dialogue-act
matching, using a custom
classifier

Models

Comparison of evaluated Language Models. SFT = Supervised Fine-Tuning

Metrics	Mistral-7B-v0.1	Gemma 2 9B	Dolphin-2.9 Llama3 8B
Parameters	7.25 billion	9 billion	8 billion
Release	2023	2024	2024
Pre-training Data	RefinedWeb (approx. 1.6 T tokens)	Google web crawl (approx. 8 T tokens, proprietary)	Meta LLaMA 3 corpora (proprietary)
Fine-tuning Data	Publicly released instruction datasets	Teacher-distilled outputs; public instruction corpora	ShareGPT, UltraChat
Fine-tuning Methods	SFT	Knowledge distillation + SFT	SFT, function-calling support

Inference & Metrics

top_k = 1
temperature = 1.0
max_length = 128
context window = 2048

Accuracy
overall correct predictions

Precision
 $Precision = \frac{TP}{TP + FP}$
correct positives among predicted positives

Recall
 $Recall = \frac{TP}{TP + FN}$
correct positives among actual positives

F1 (macro)
average of per-class F1s

DA Alignment
match rate of predicted vs. GT dialogue acts
(Experiment II)

F1 (micro)
global TP/FP/FN aggregation

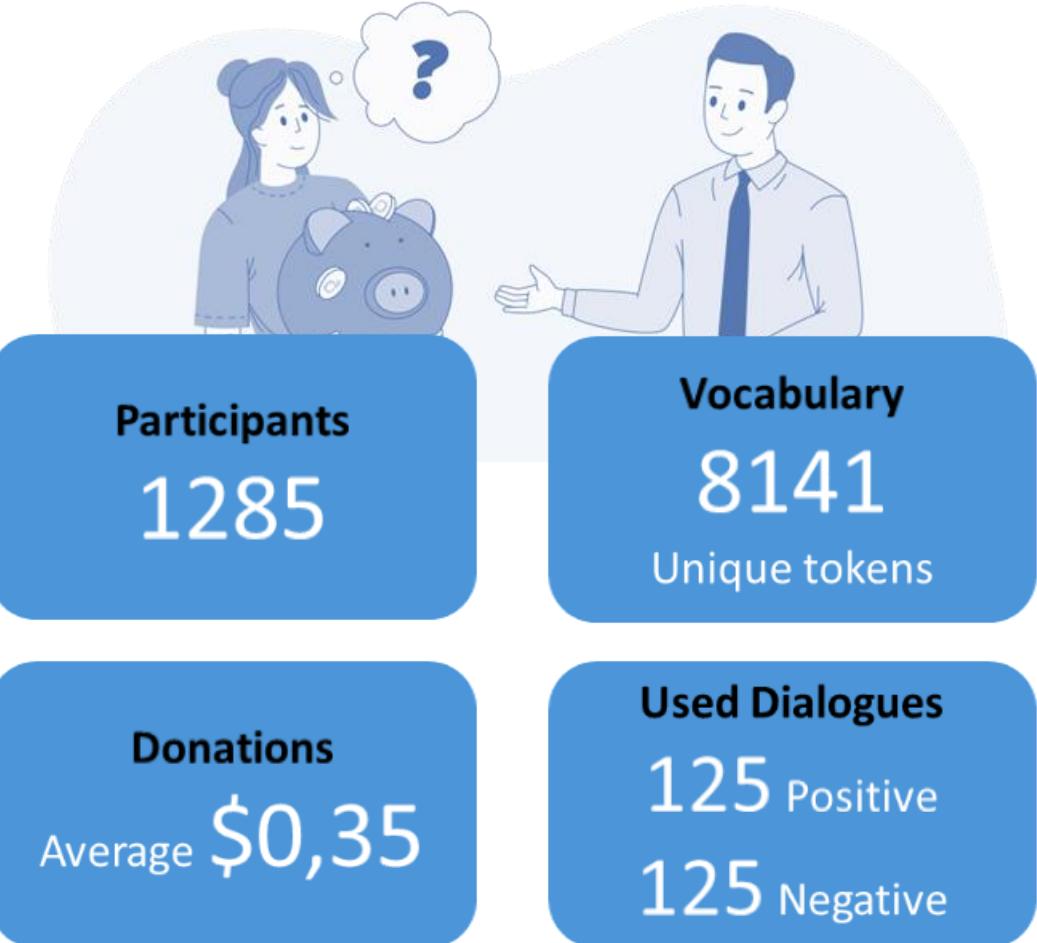
Experiment I

Design

- Dialogues truncated to different lengths (e.g., 7 turns, 11 turns, full history)
- Final persuadee decision removed → LLM asked to predict:
 - Binary decision: donate or not
 - Donation amount (numeric value)
- Setup isolates whether LLMs can extrapolate **implicit decision-making cues** from dialogue context

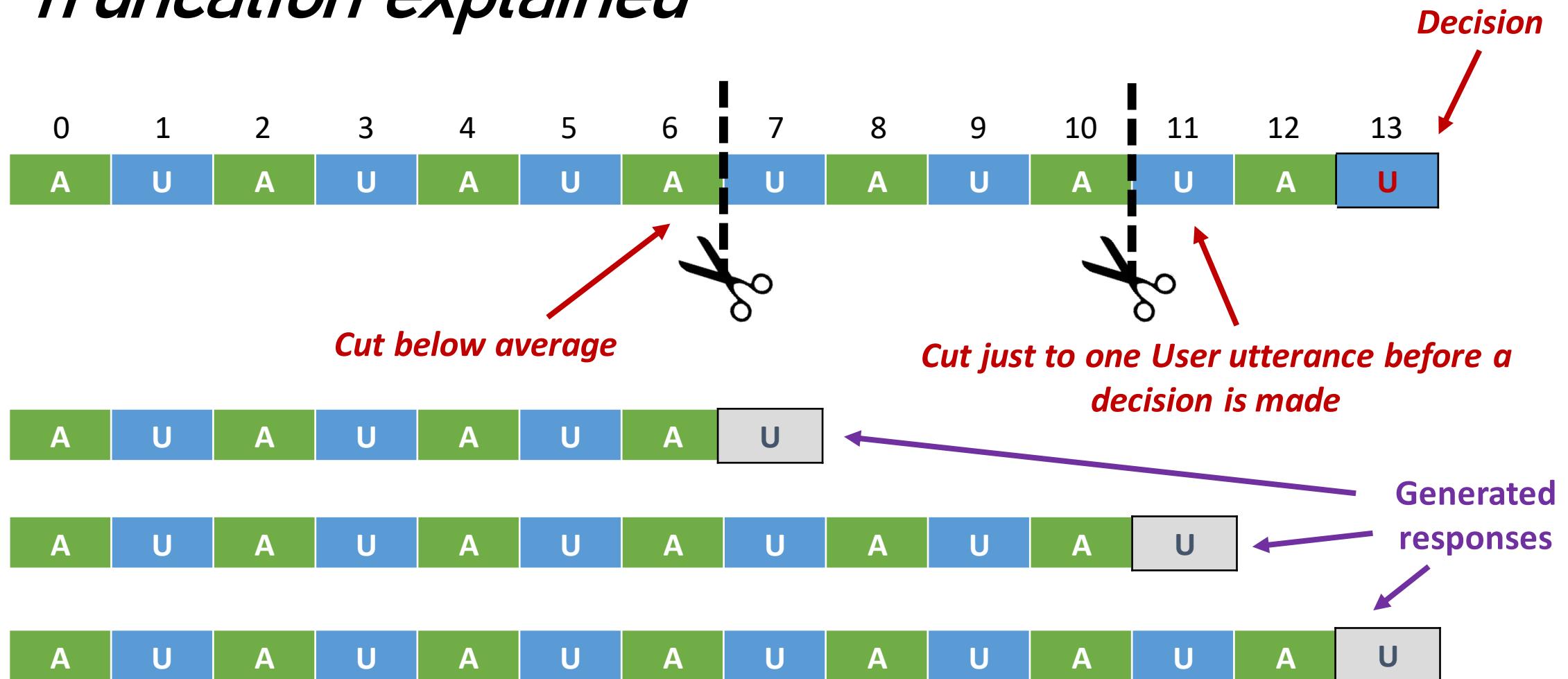
Dataset I

Persuasion for Good



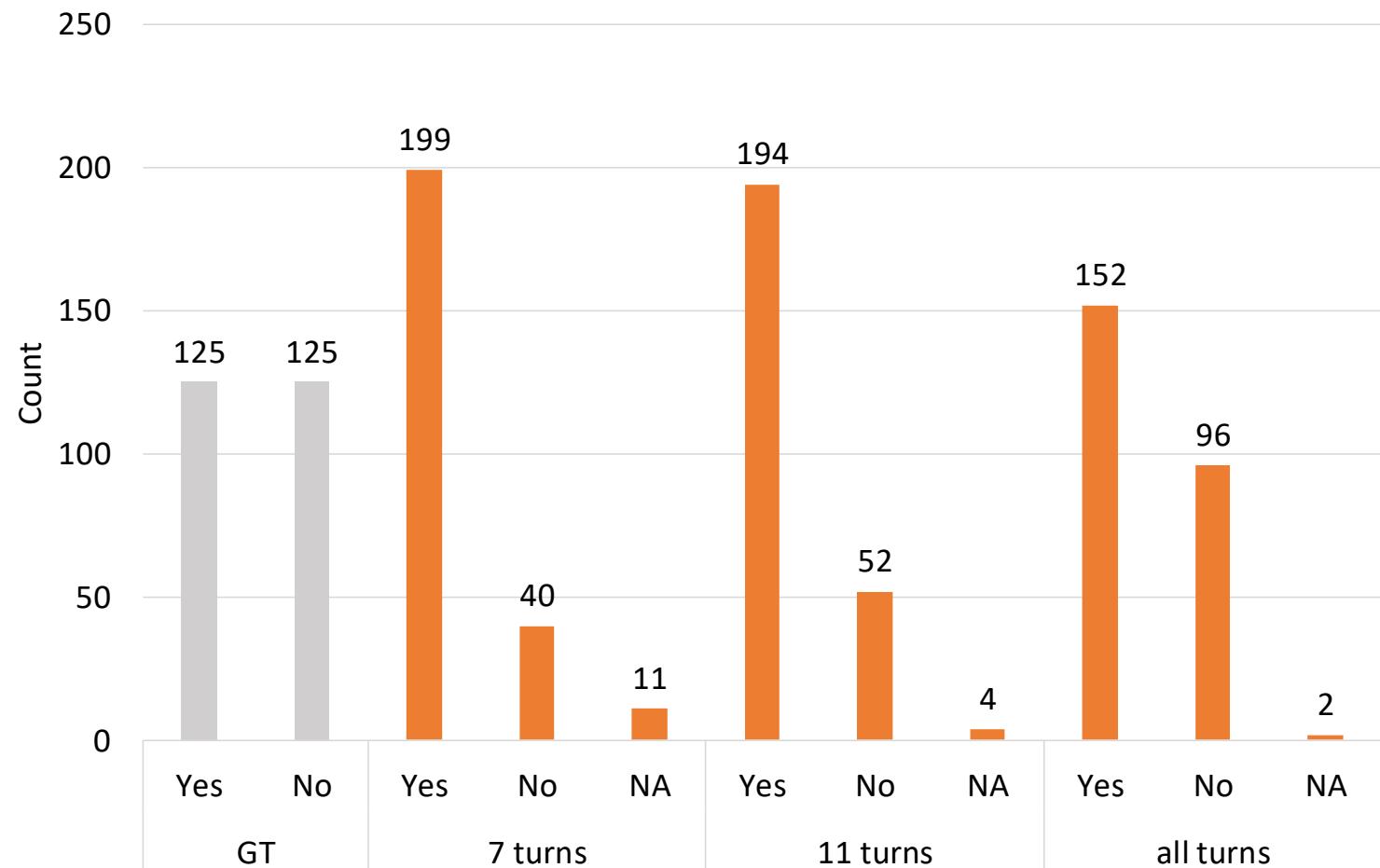
Experiment I Setup

Truncation explained



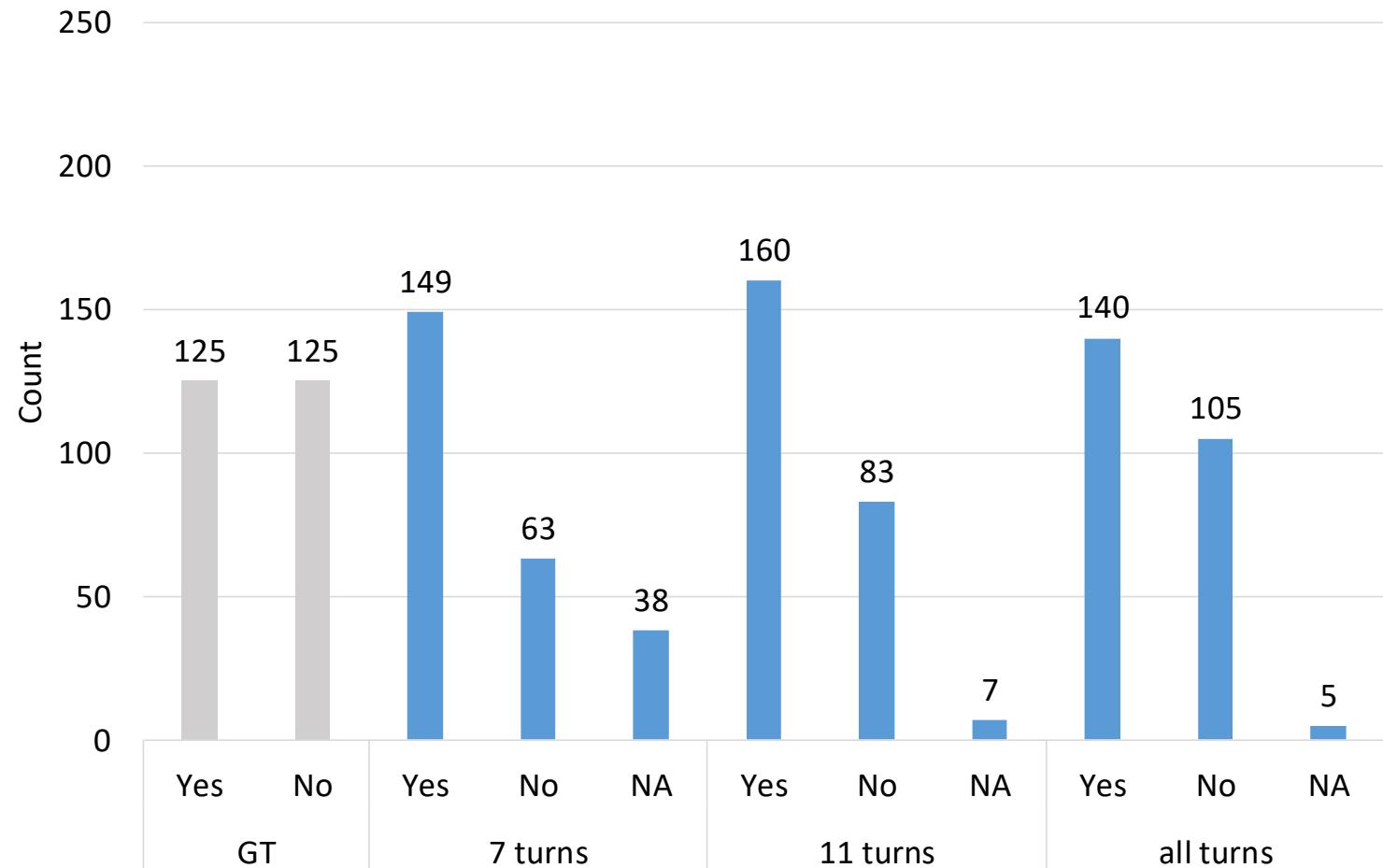
Experiment I: Yes/No Decision

Mistral



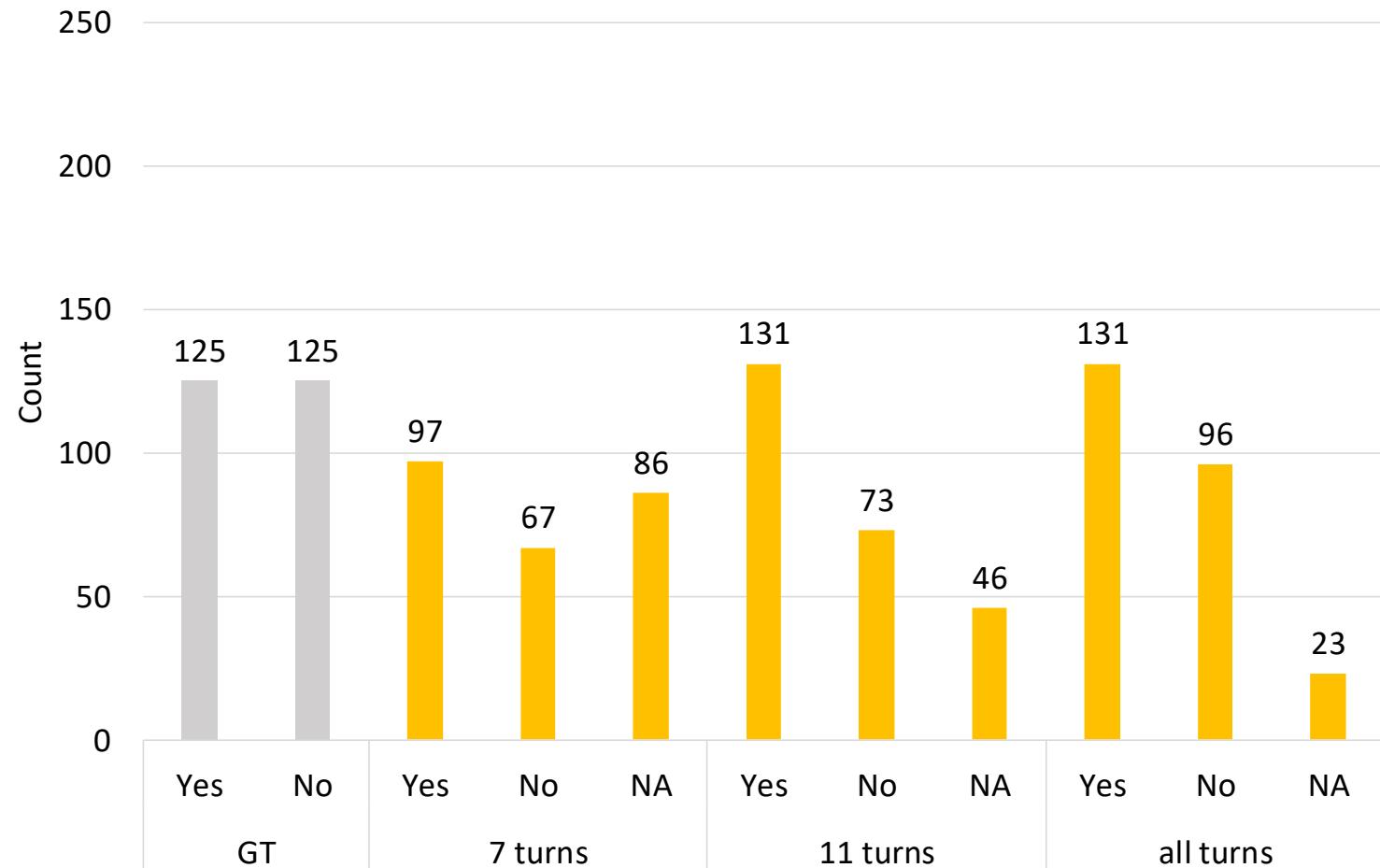
Experiment I: Yes/No Decision

Gemma 2

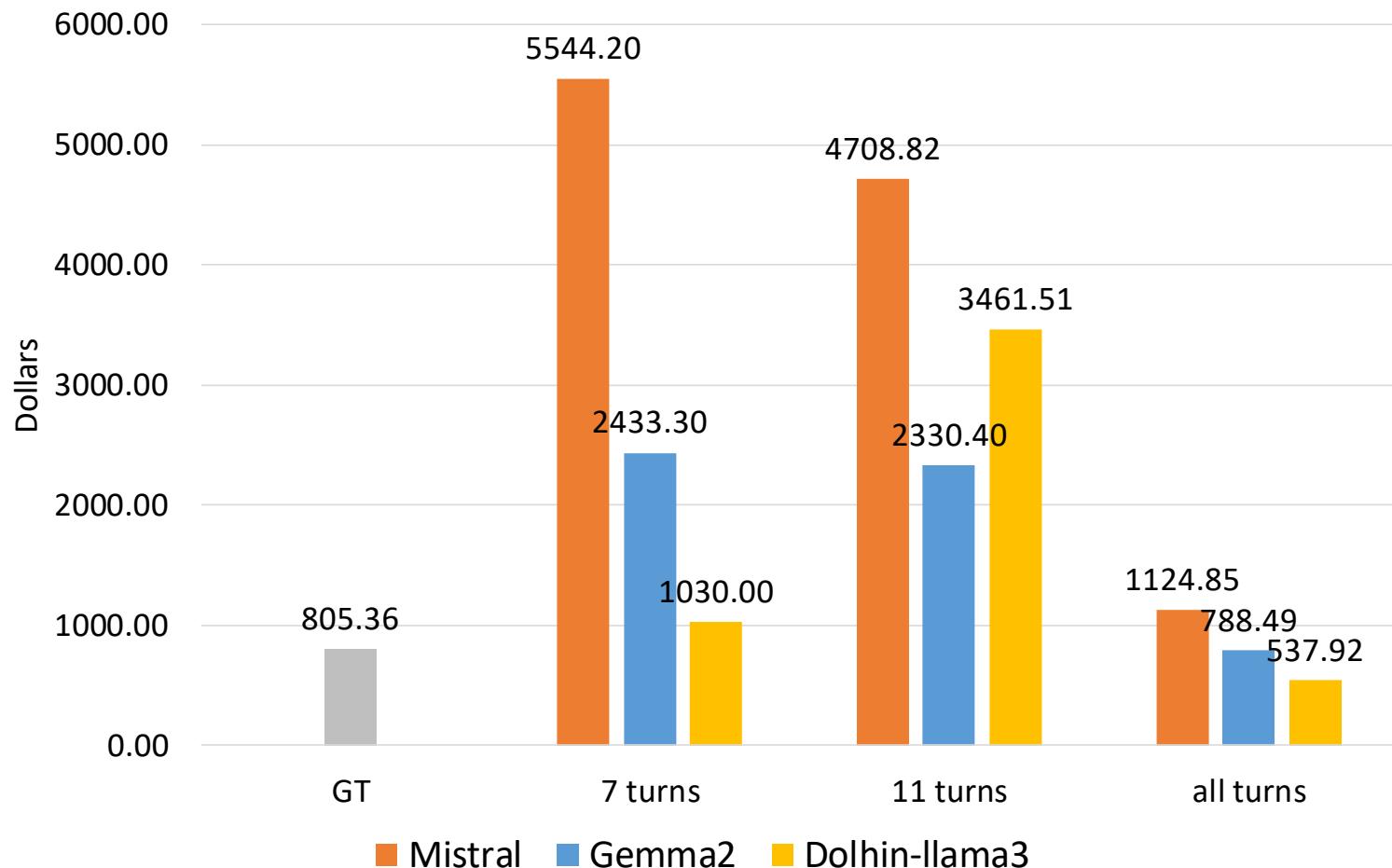


Experiment I: Yes/No Decision

Dolphin-Llama 3



Experiment I: Donation amounts reveal bias



Experiment II

Design

- Dialogues truncated to different lengths (e.g., 6 turns, 10 turns, full history)
- LLMs were asked to generate the missing user utterance, using only the dialogue history
- A custom RoBERTa-based multi-label Dialogue Act classifier was developed precisely for the 20 labels used in the dataset
- Generated utterances were classified with a developed DA classifier
- The Ground Truth Das were compared to Generated DAs

Dataset II

Frames



Dialogues
1369

Roles
- Wizard
- User

Turns
19986

Turns per Dialogue
14,6

Dialogue Length
3 – 43 turns

Dialog Acts
20

Annotation
75%: 1 DA
25%: >1 DA

Used Dialogues
1101 Train
268 test

Experiment II Setup

Generating the user's next turn



Generated responses:



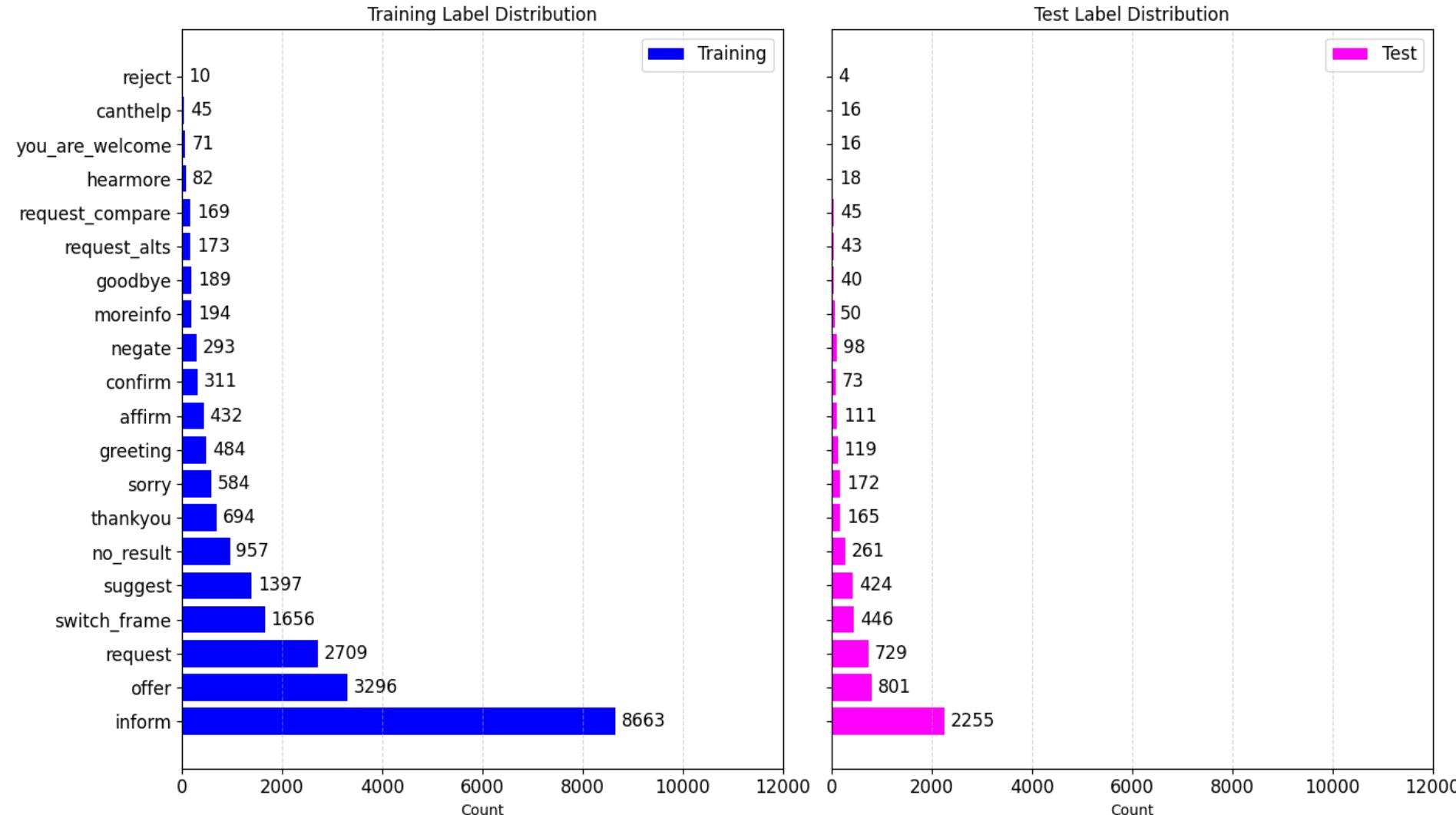
Average utterance number through the selected dialogues is equal 14

Dialogue Acts

Dialogue Act	Speaker	Description
<i>inform</i>	User/Wizard	Inform a slot value
<i>thankyou</i>	User/Wizard	Thank the other speaker
<i>no_result</i>	Wizard	Tell the user that the database returned no results
<i>sorry</i>	Wizard	Apologize to the user
<i>goodbye</i>	User/Wizard	Say goodbye to the other speaker
<i>negate</i>	User/Wizard	Negate something said by the other speaker
<i>you_are_welcome</i>	Wizard	Tell the user they are welcome
<i>suggest</i>	Wizard	Suggest a slot value or package that does not match the user's constraints
<i>switch_frame</i>	User	Change the topic
<i>affirm</i>	User/Wizard	Affirm something said by the other speaker

Dialogue Act alignment after pre-processing

Train VS Test



Dialogue Act Classifier

Why create a custom classifier?

- Frames dataset → 20 dialogue act labels
- No suitable classifier available

How was it built?

- RoBERTa encoder + multi-label head
- Binary cross-entropy loss
- Iterative stratification → balanced labels

Performance & Role:

- F1: Train 0.93 / Validation ~0.58
- Classifies both human & LLM utterances
- Backbone for Experiment II evaluation

suggest

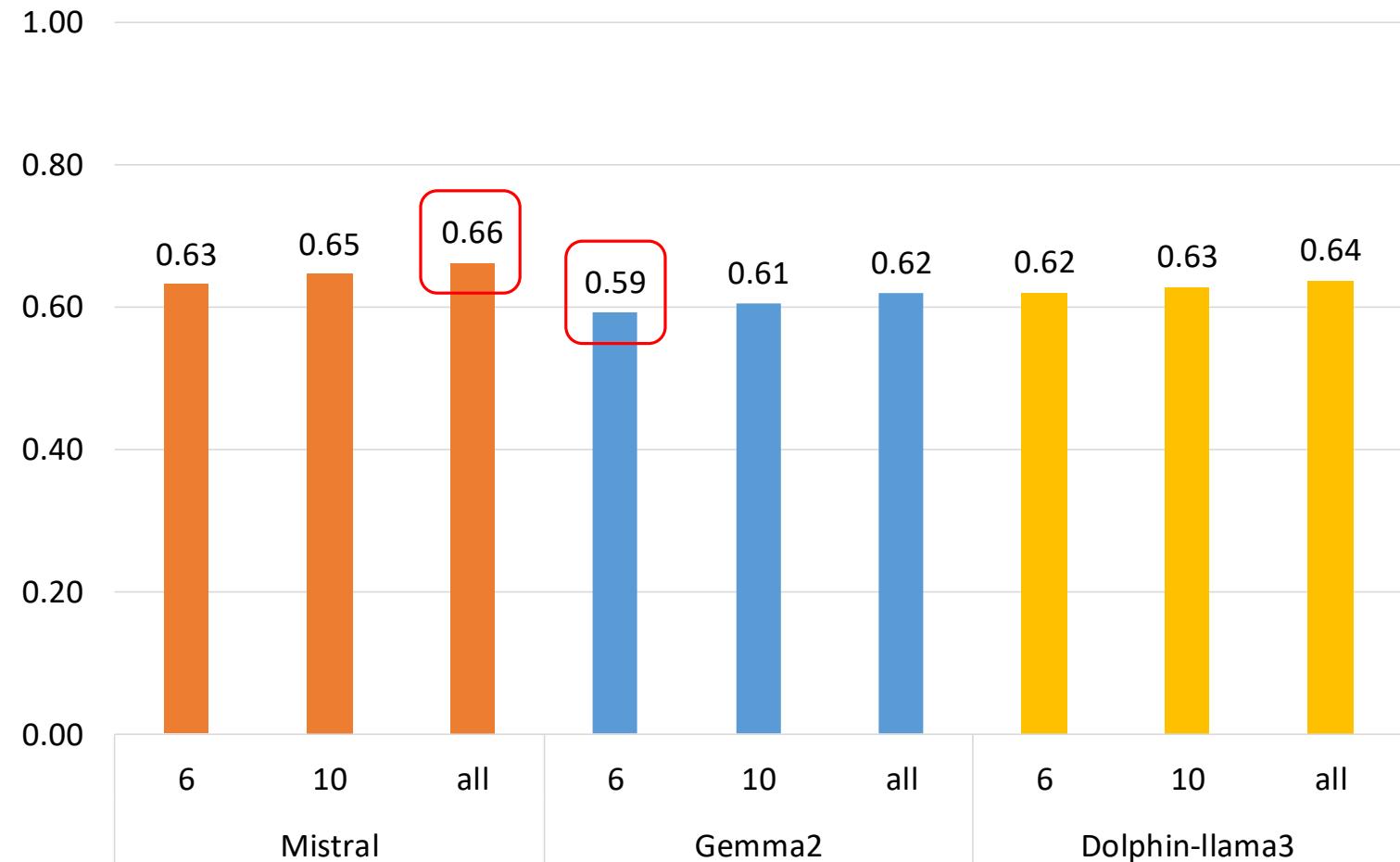
inform

affirm

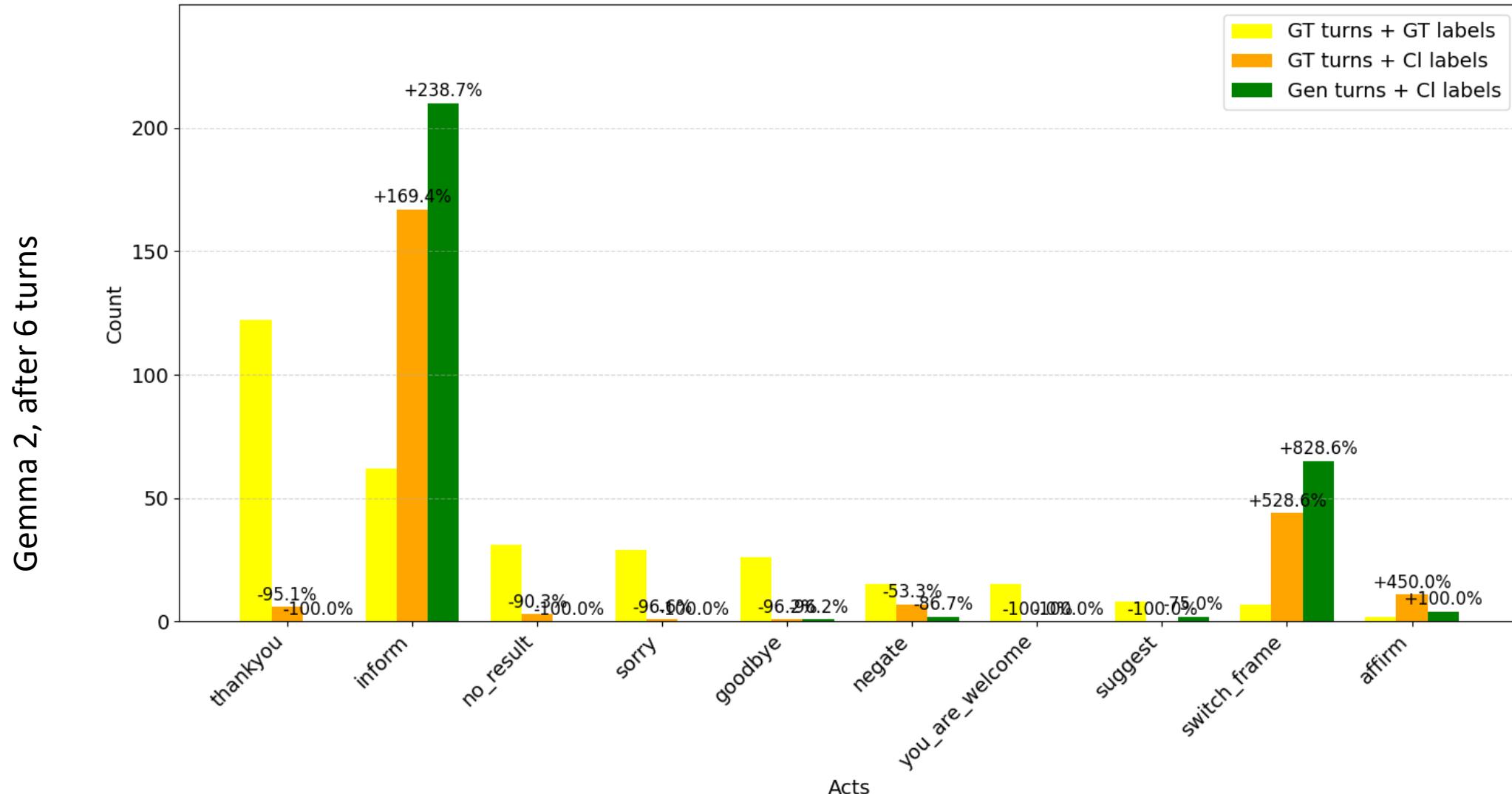
no_result

goodbye

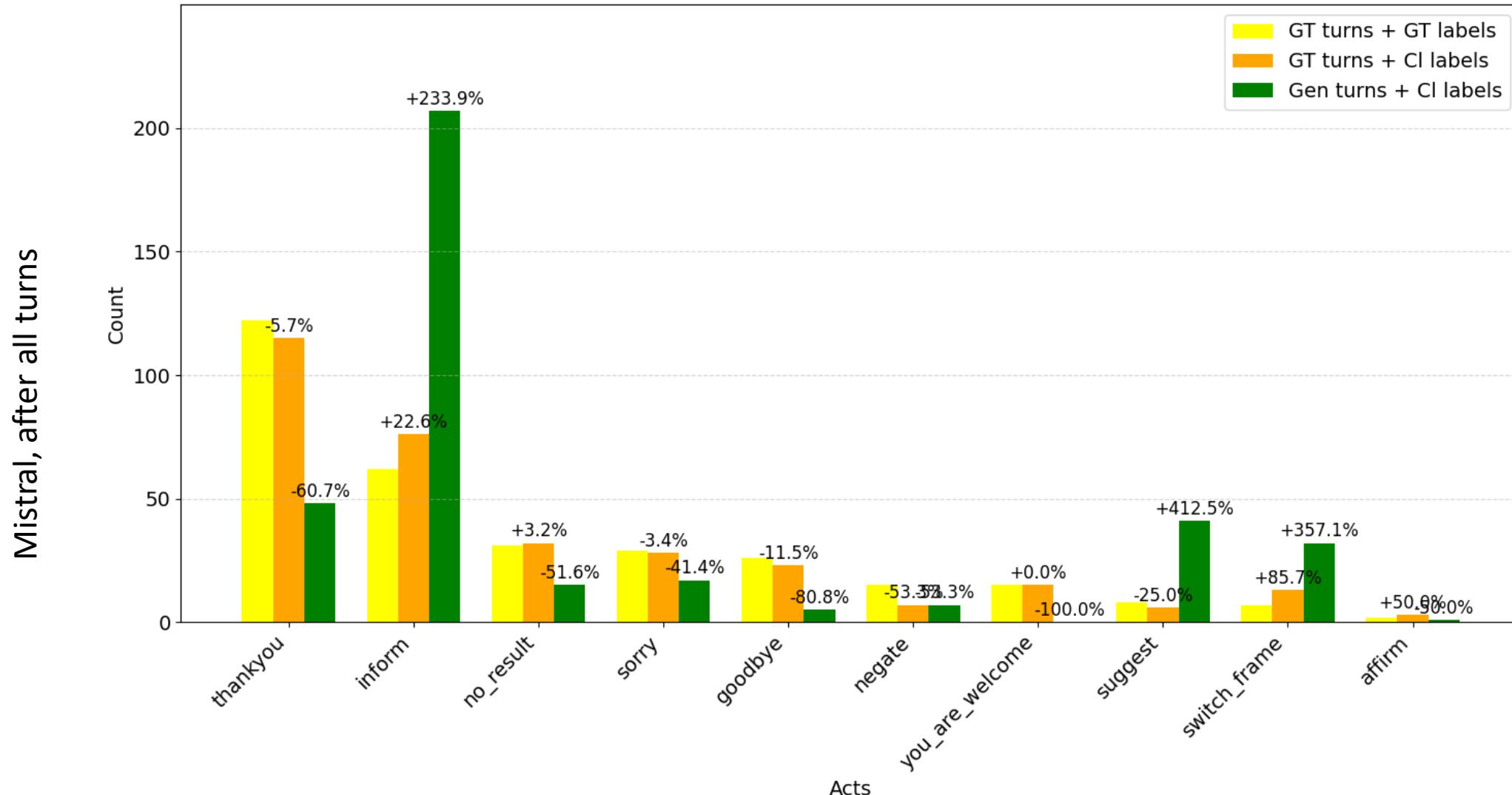
F1-Macro for generated results of all LLMs after 6, 10 and all utterances



Experiment II Results



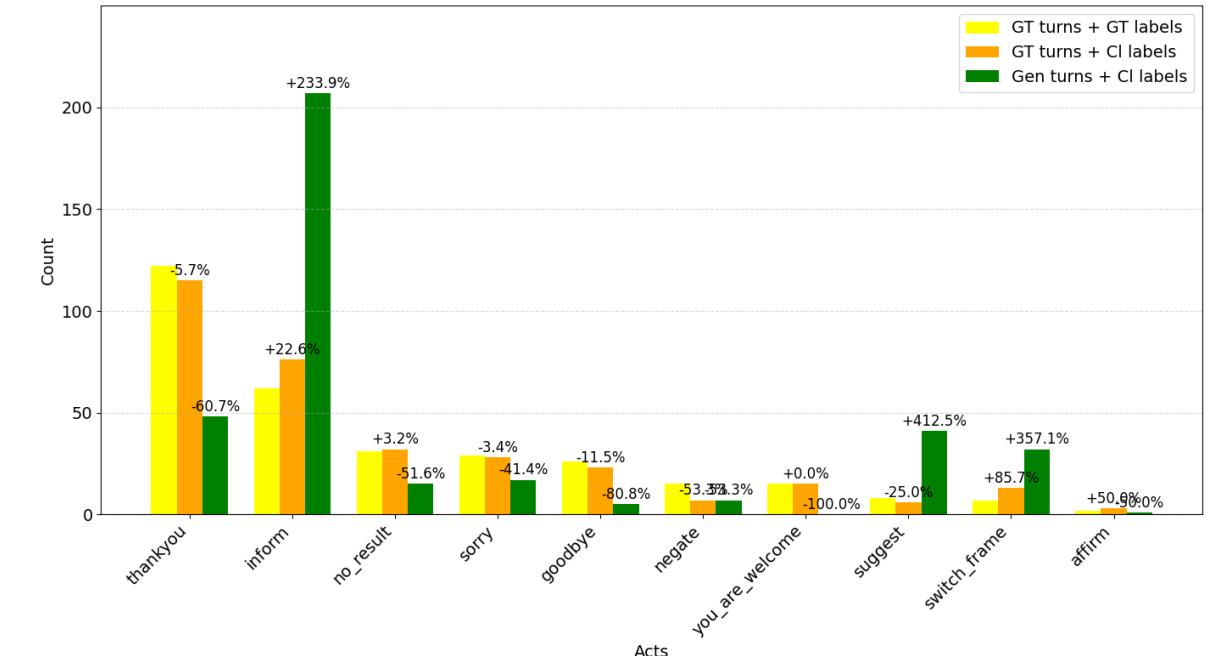
Experiment II Results



Where models fail

- Affirmative bias + Donation amount inflation (“Yes” answers in Experiment I)
- Dialogue Act over/under-shoot (Experiment II)

Under-produce
 Over-produce



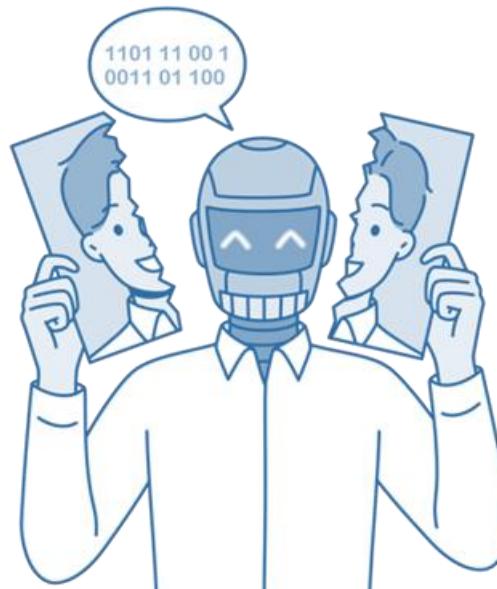
Key Findings

Can LLMs predict a persona's decision from dialogue history?

- Partially: accuracy improves with longer context;
- But → strong *affirmative bias*, inflated donation amounts, unsuitable dialogue acts that don't match the dialogue history.

How much history is needed?

- Approximately 10-11 turns are sufficient for coherent, somewhat persona-aligned outputs.



Can LLMs generate next utterances aligned with persona's actions?

- Syntax: plausible;
- Semantics: limited alignment with ground truth;
- Experiment II → F1 < 0.66; missing social acts like *thankyou* and *goodbye*.

Limitations & Future Work

- Open-weight mid-size models only
- Reliance on automated DA labelling
- Only two domains (donations, travel)
 - Task-specific fine-tuning and calibration
 - Hybrid symbolic-neural approaches for reasoning
 - Richer human-in-the-loop evaluation of persona alignment

Conclusion

Current LLMs mostly echo surface patterns;

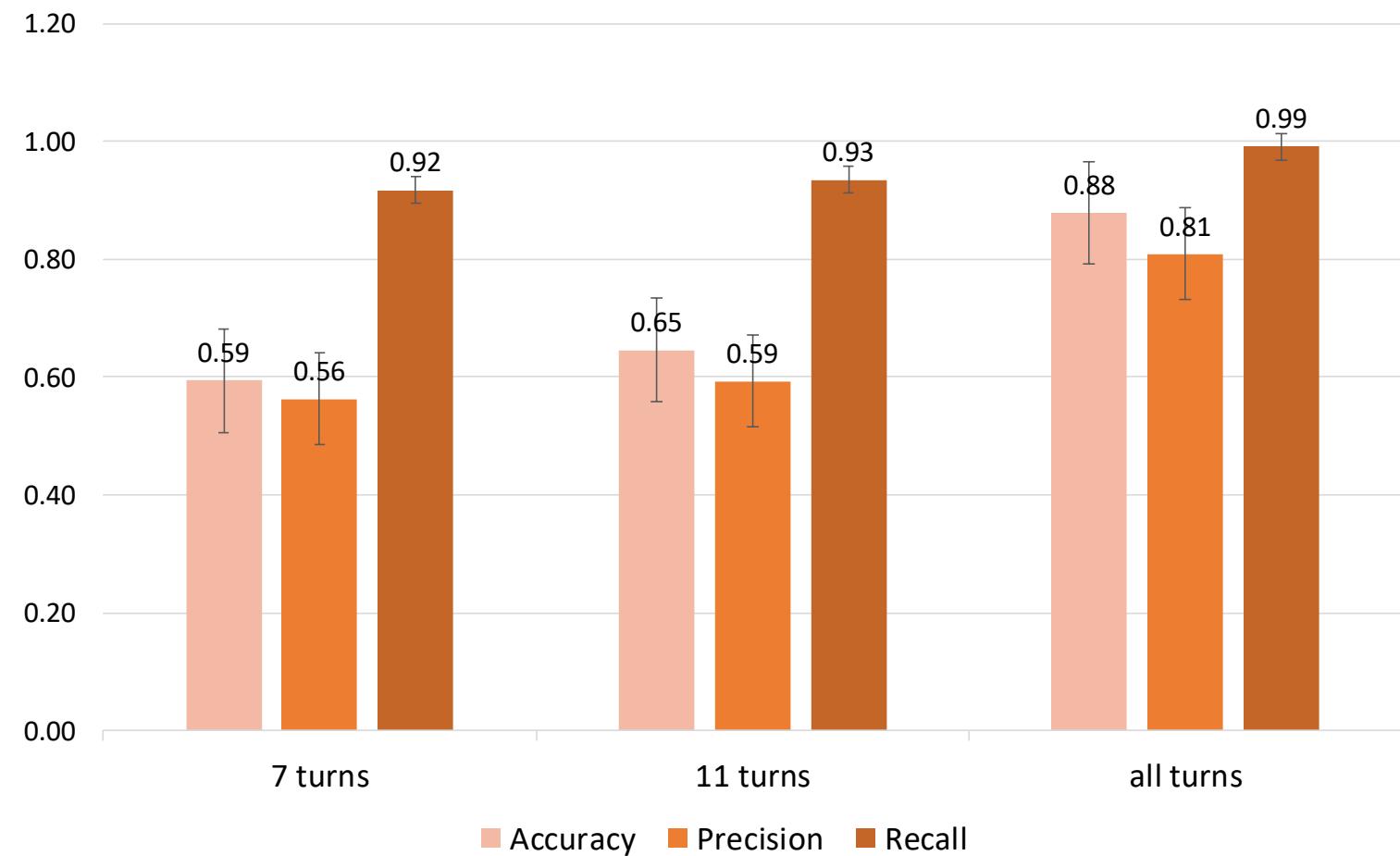
Robust persona alignment will require explicit preference elicitation, calibration, and structured (hybrid) control.

Thank you

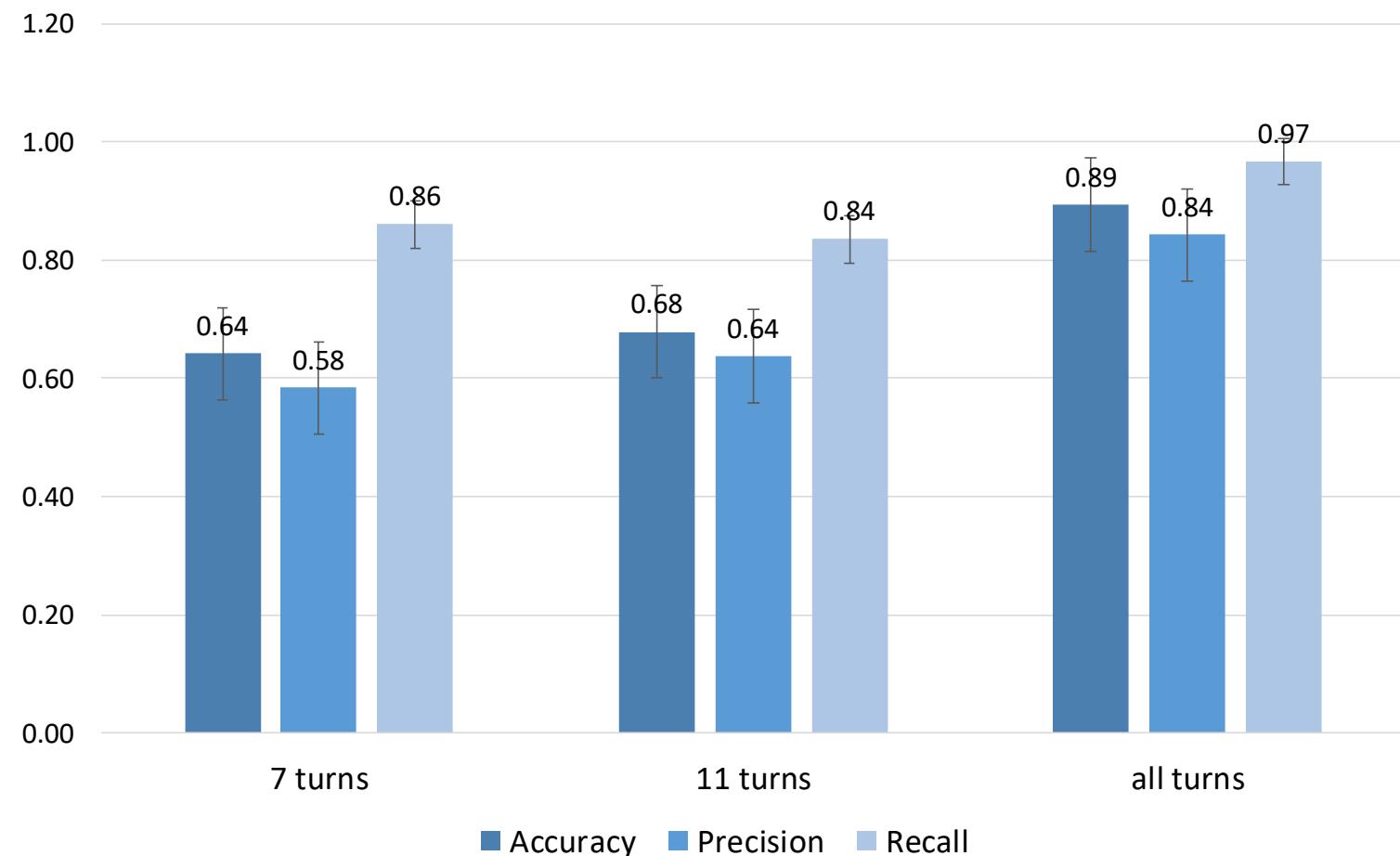
Vielen Dank für Ihre Aufmerksamkeit!



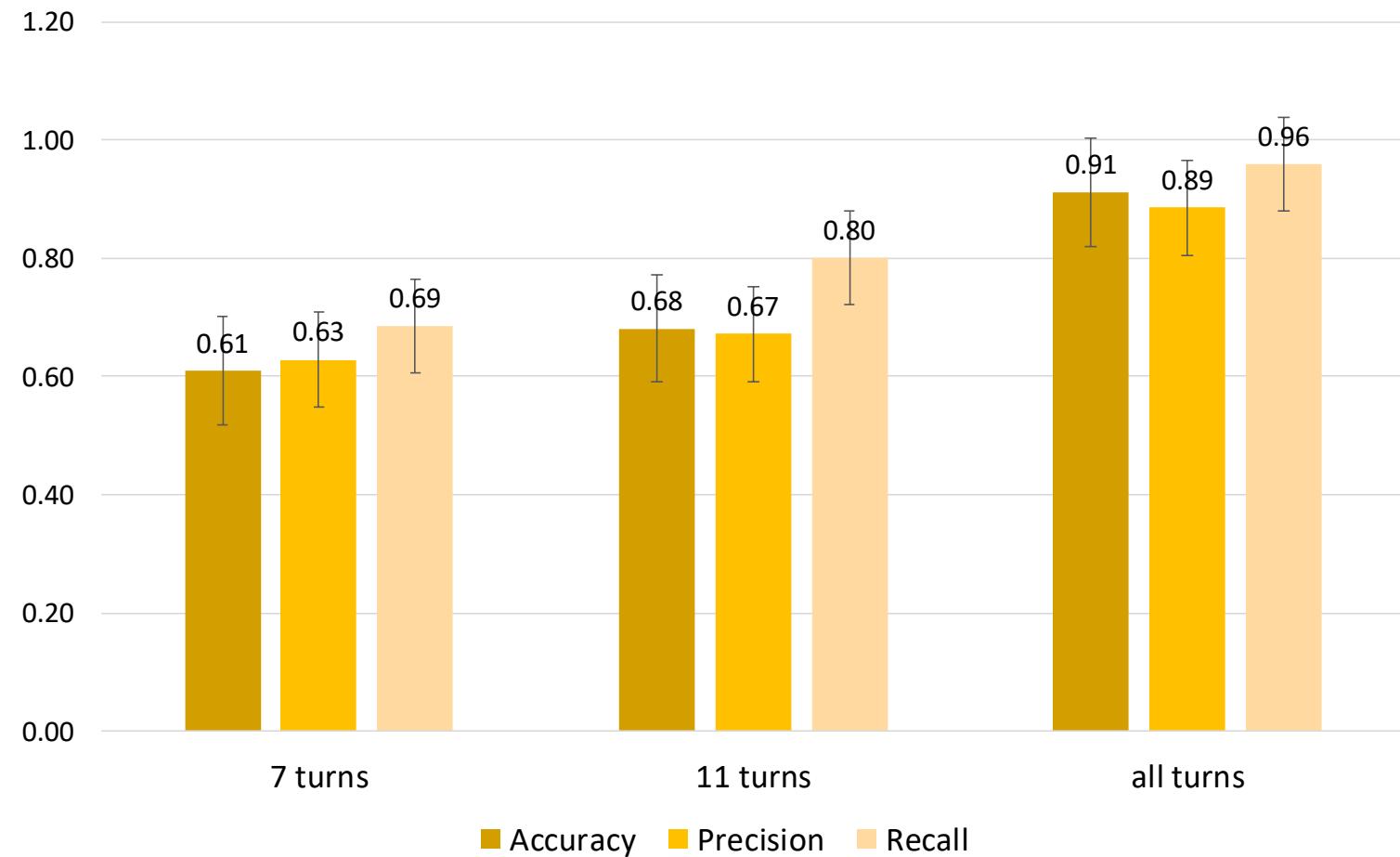
Experiment I, Mistral



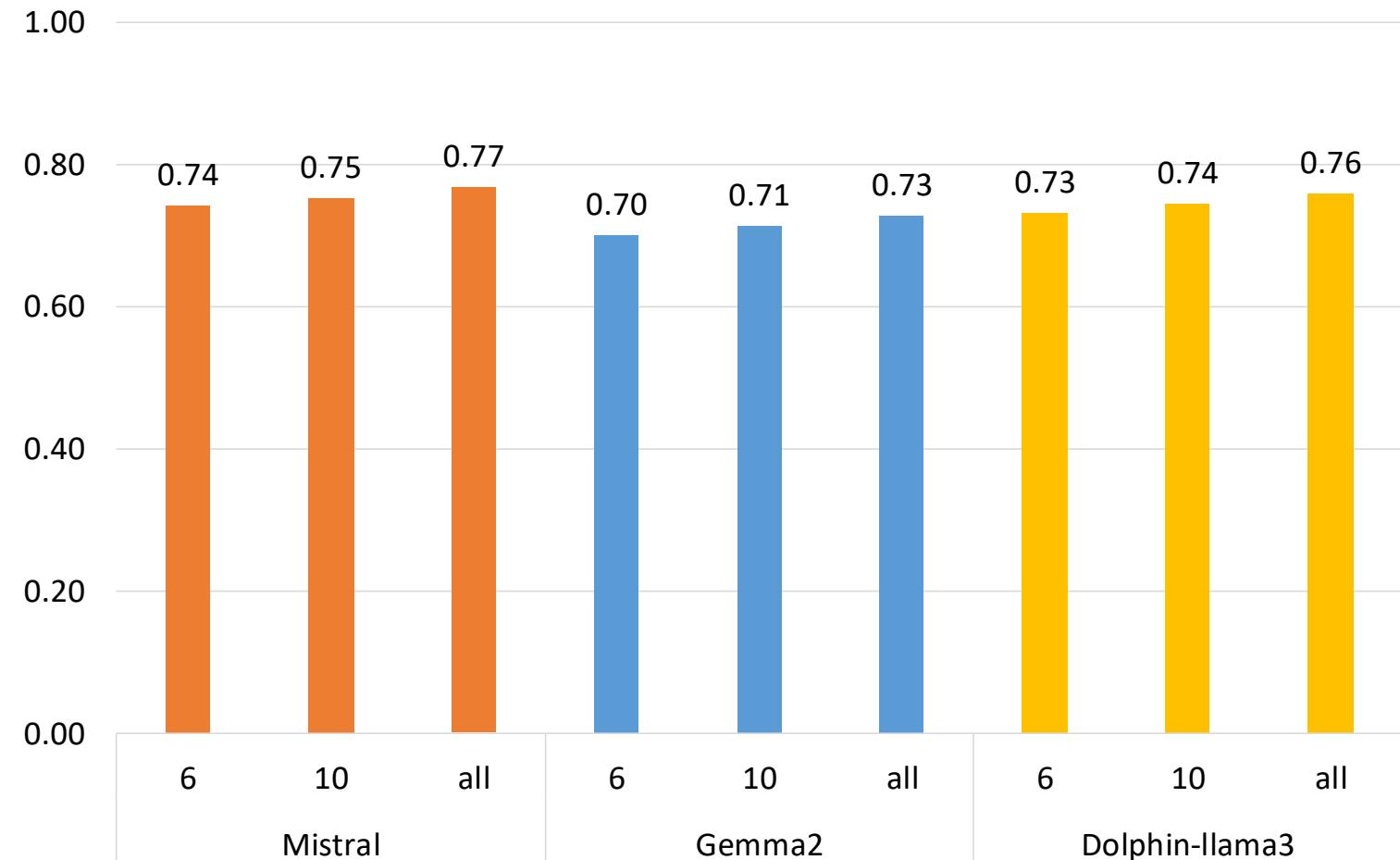
Experiment I, Gemma 2



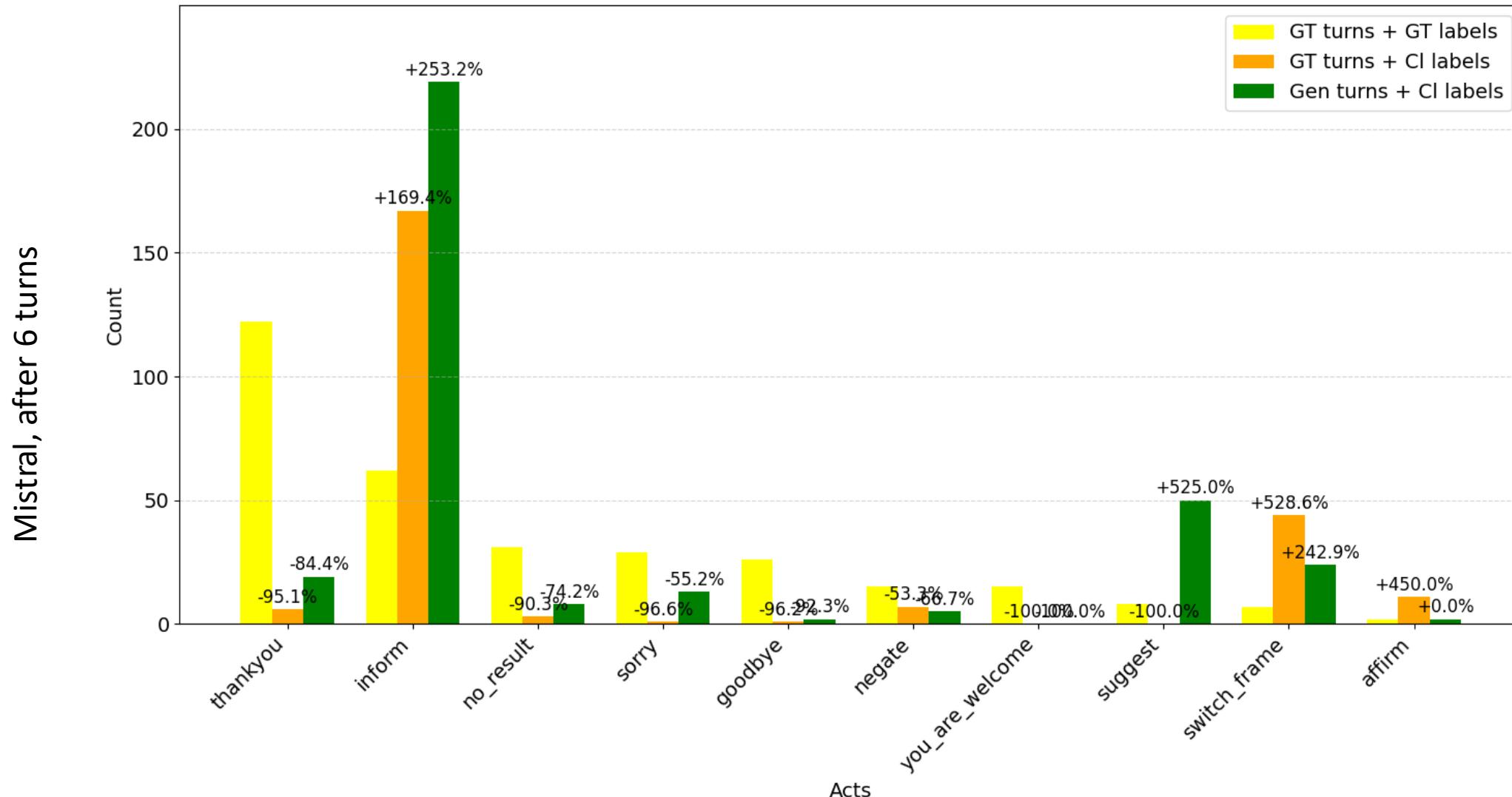
Experiment I, Dolphin-Llama 3



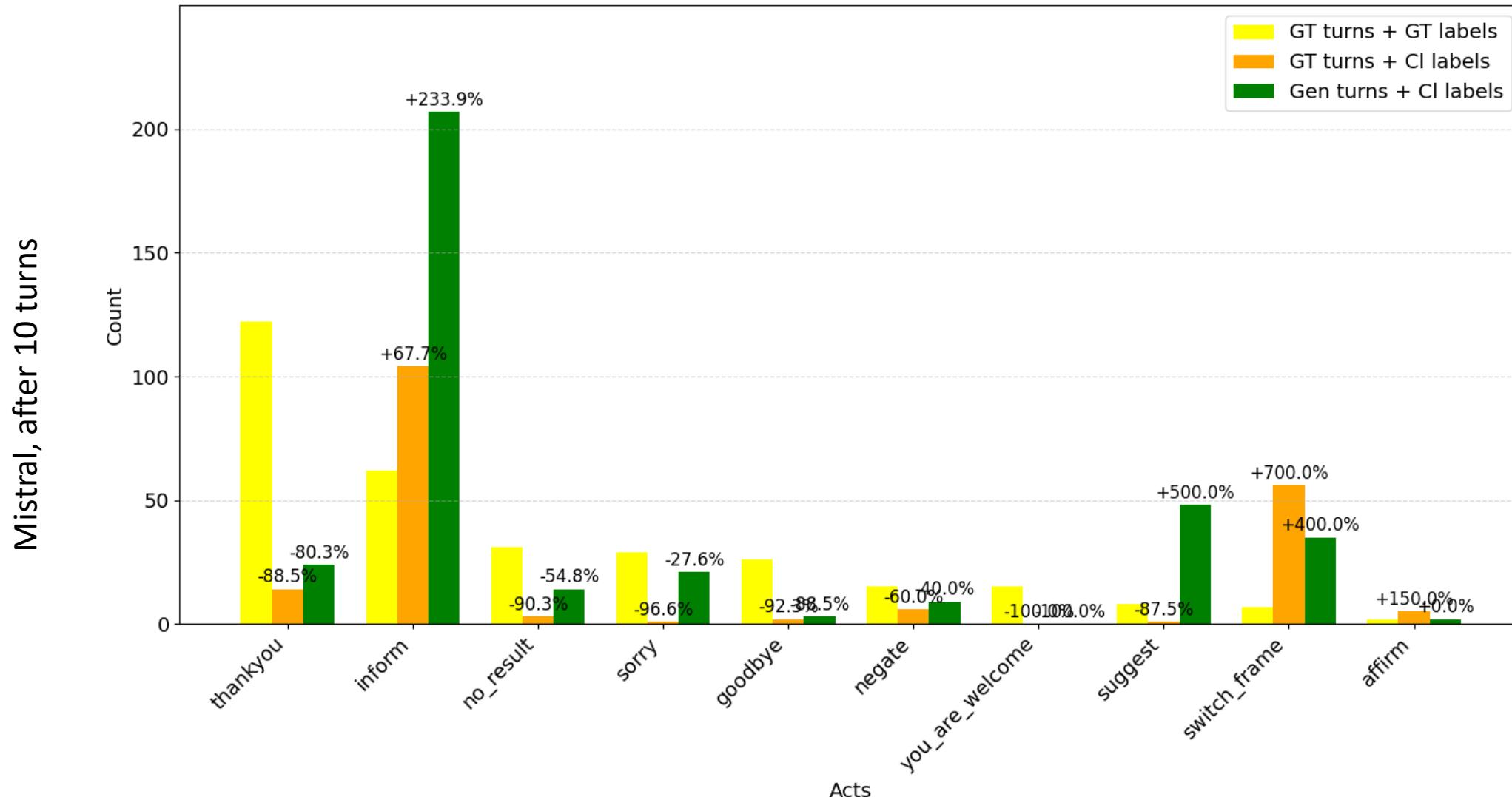
Experiment II, Micro-F1



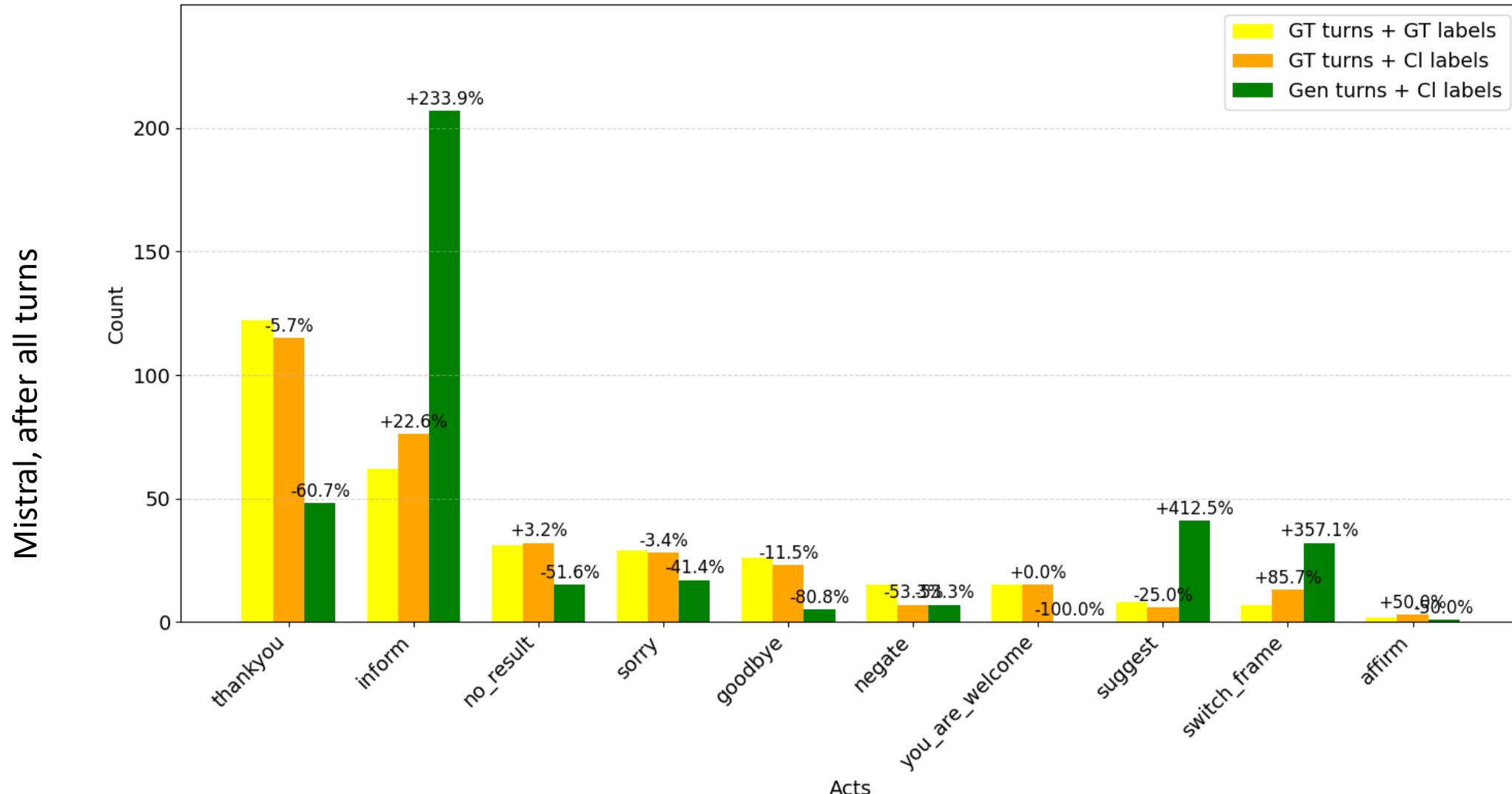
Experiment II Results



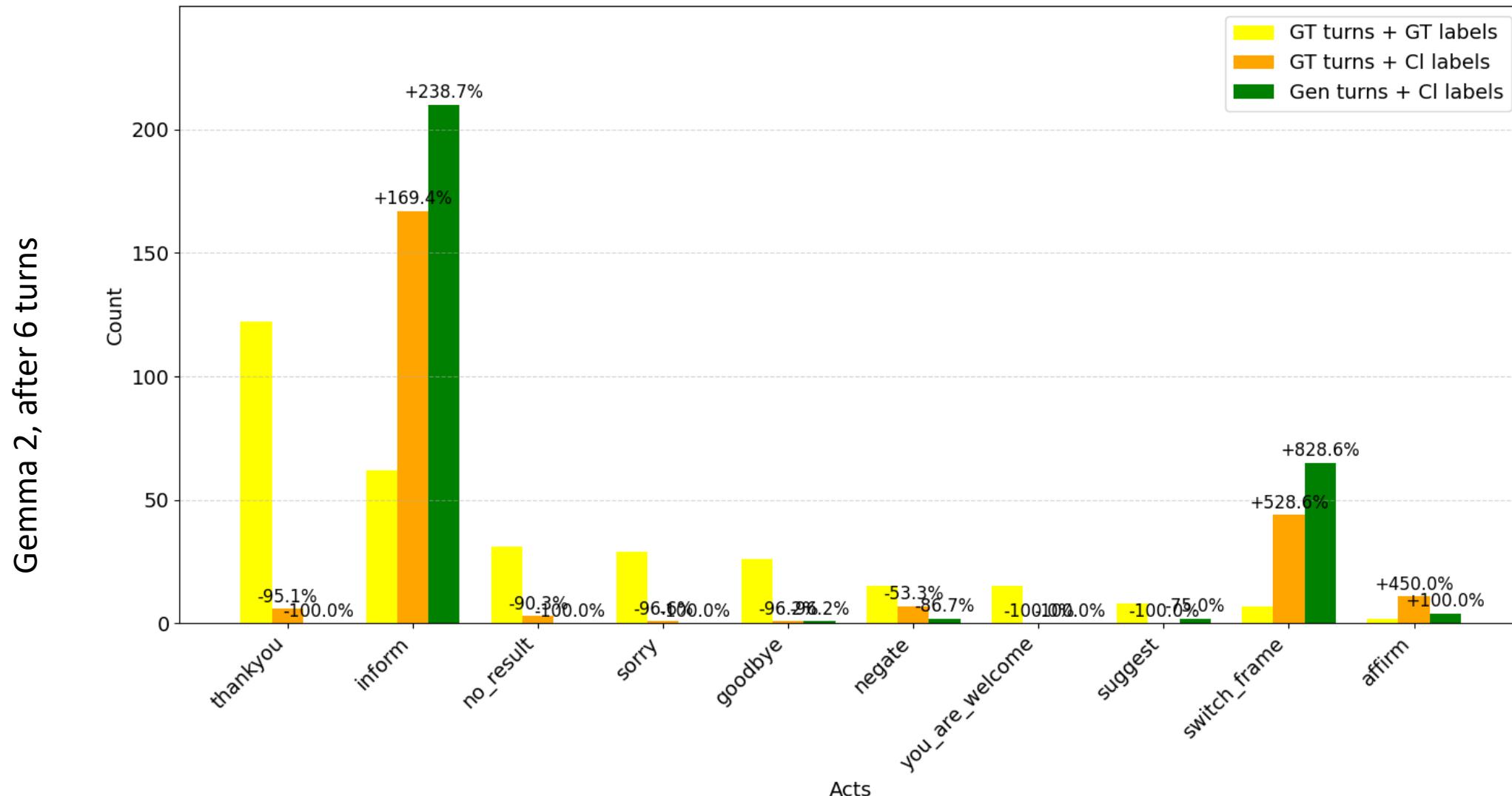
Experiment II Results



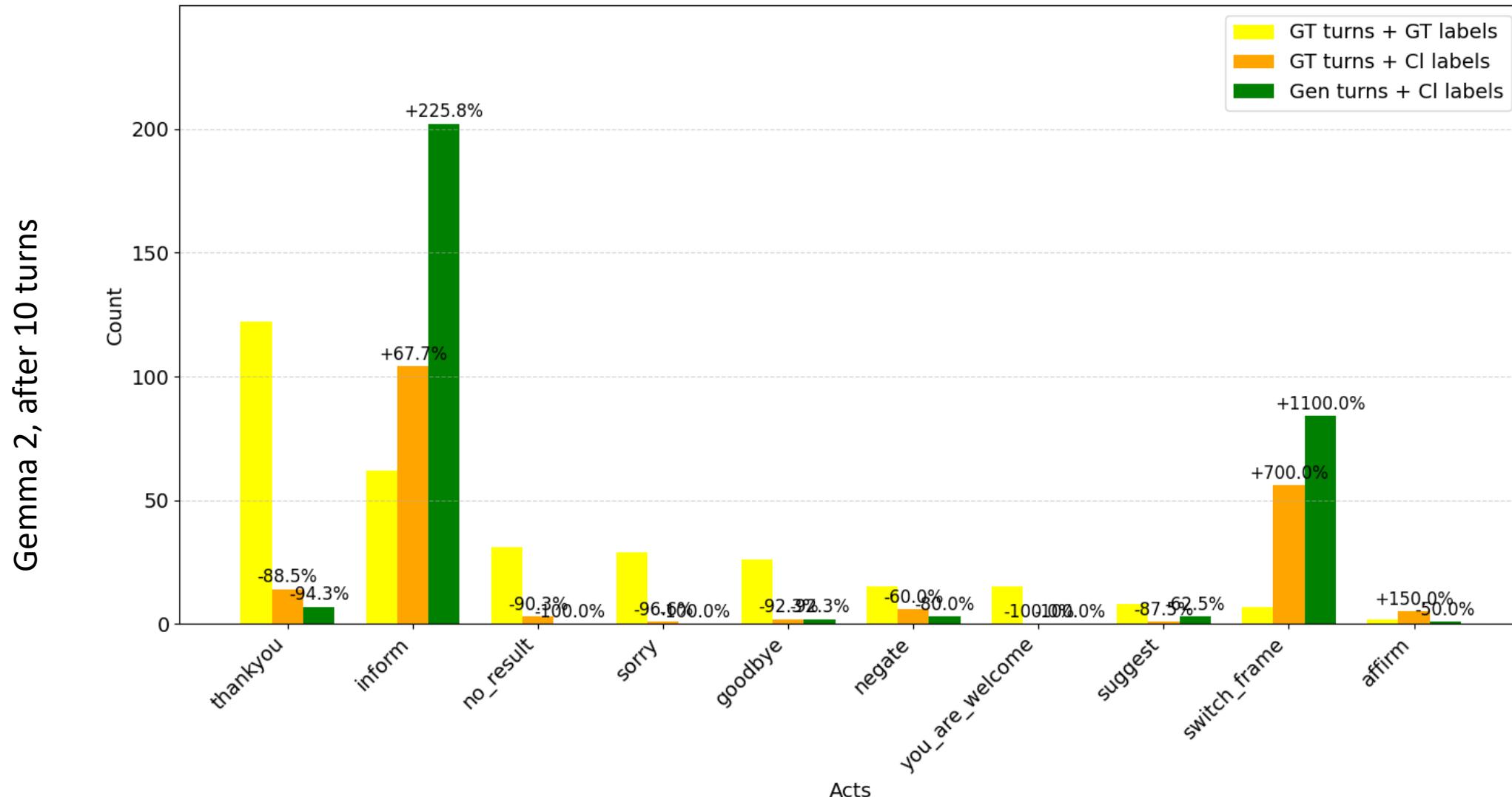
Experiment II Results



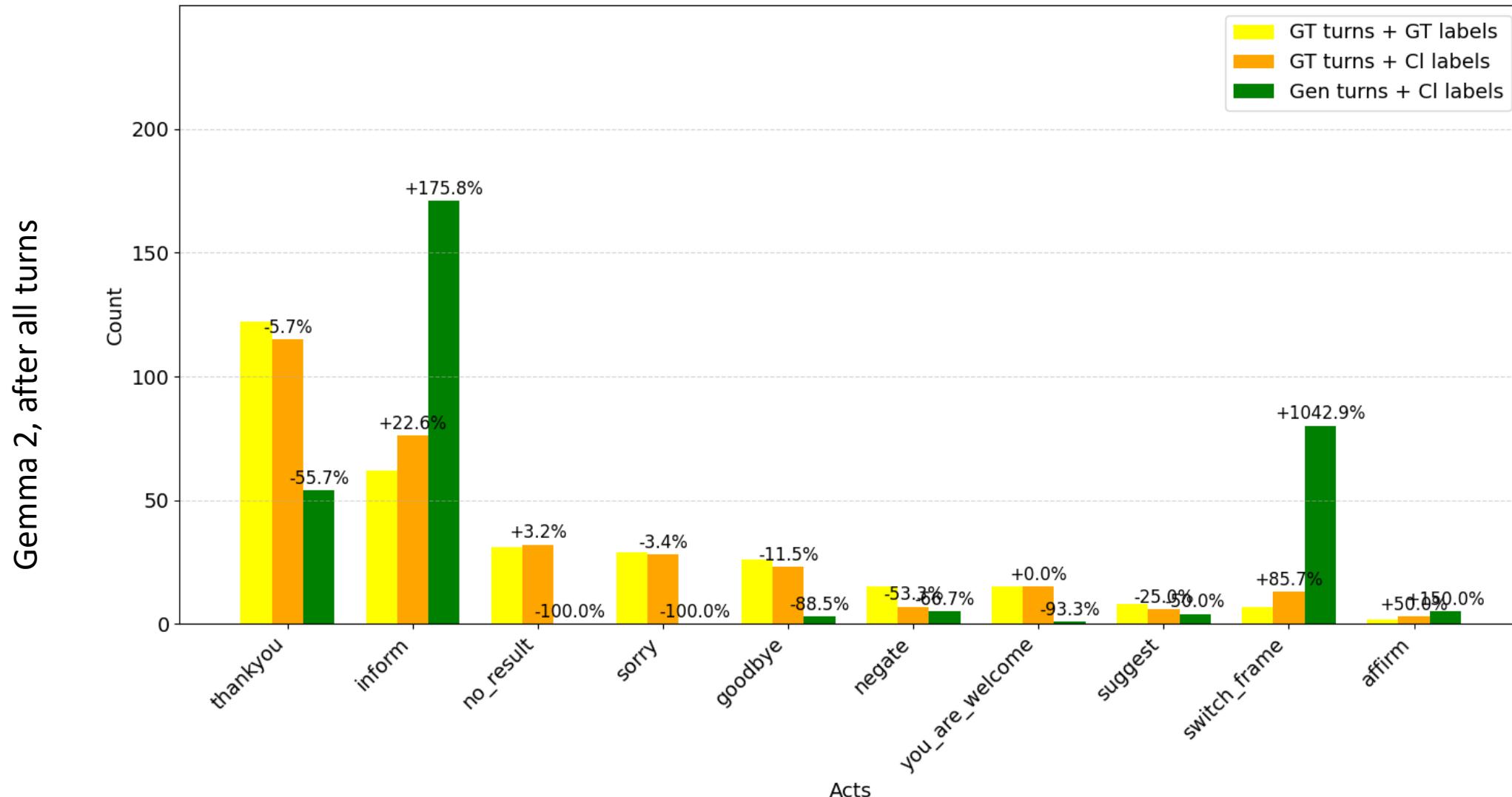
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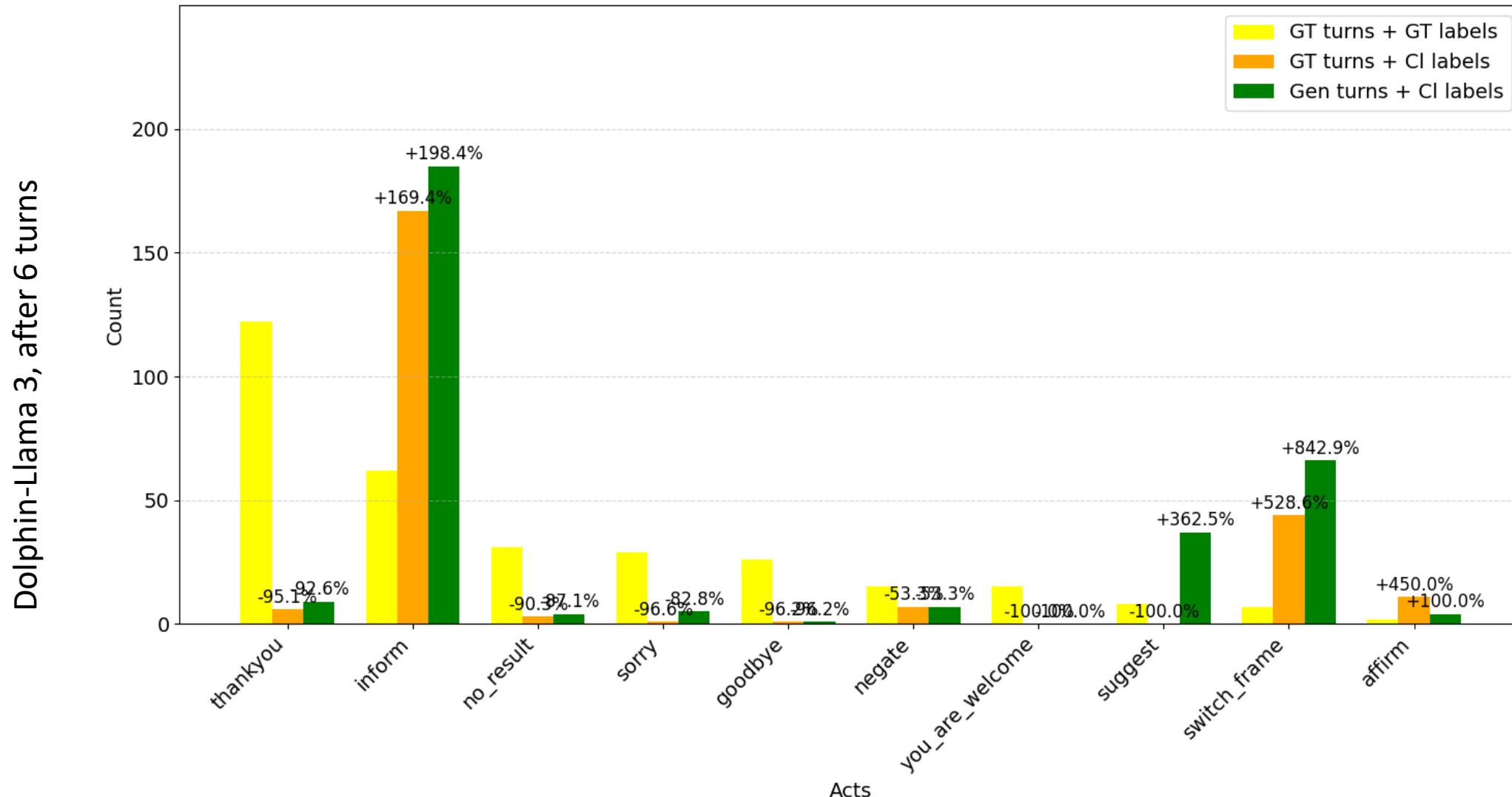
Experiment II Results



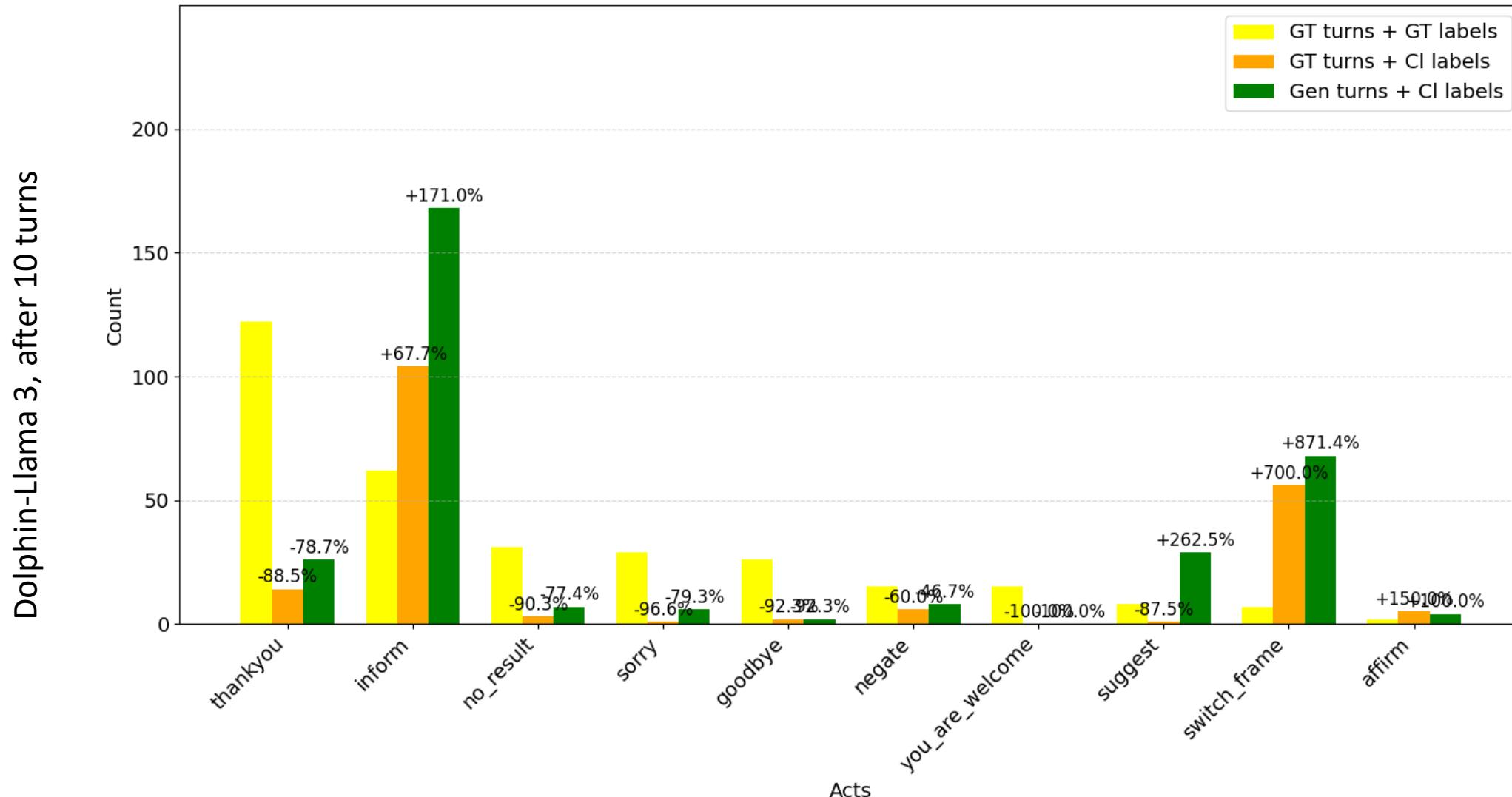
Experiment II Results



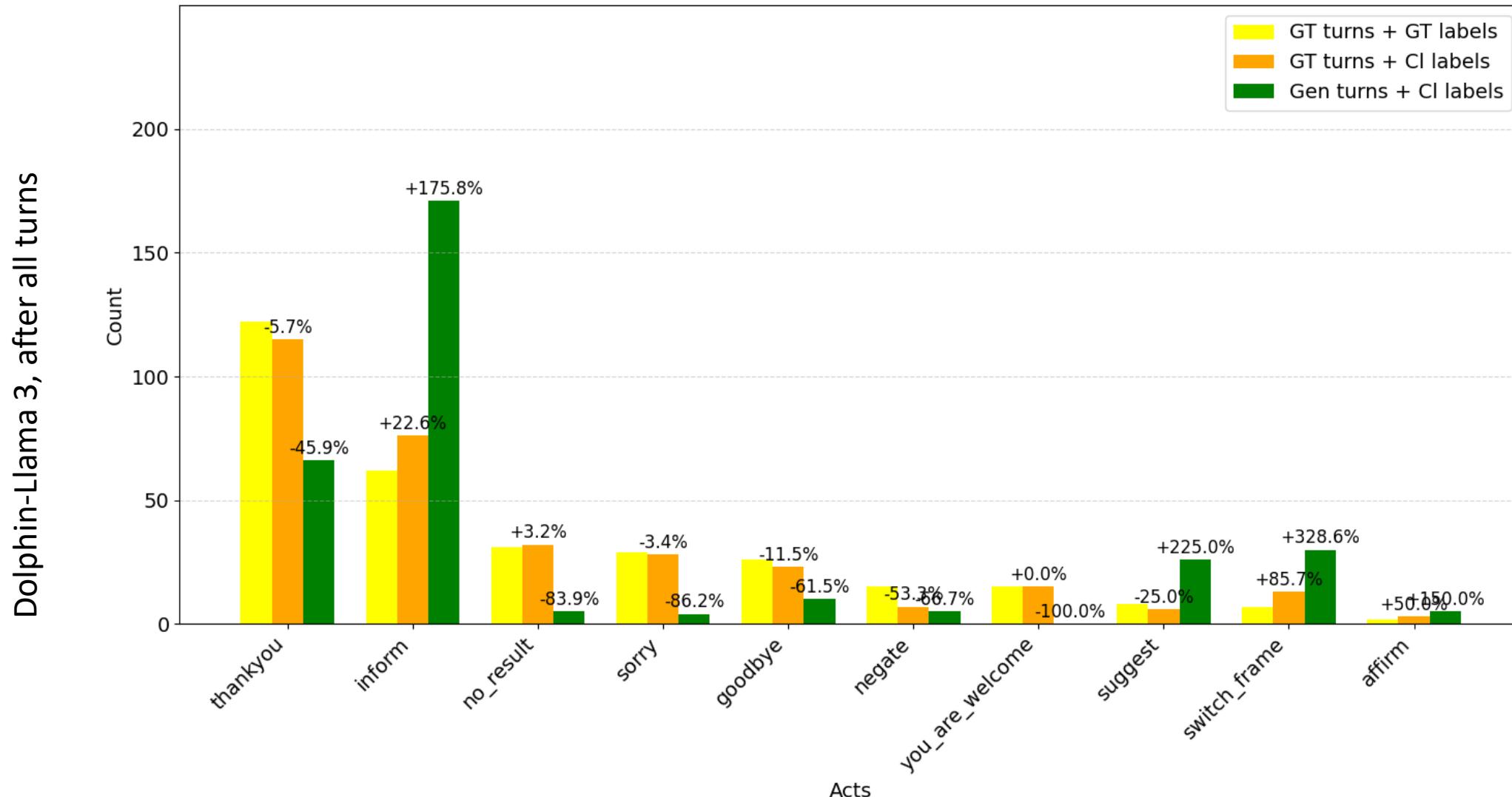
Experiment II Results



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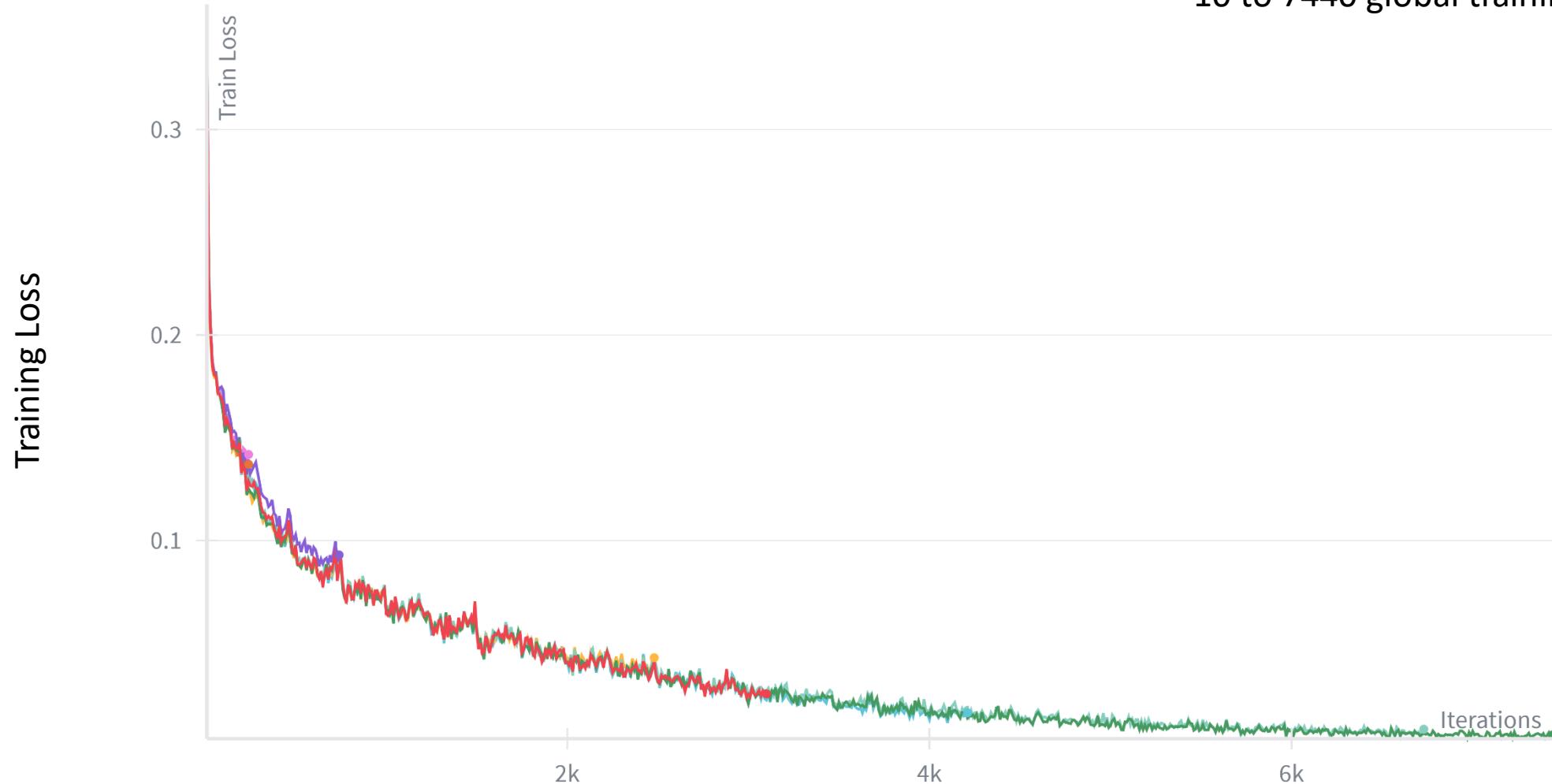


Experiment II Results

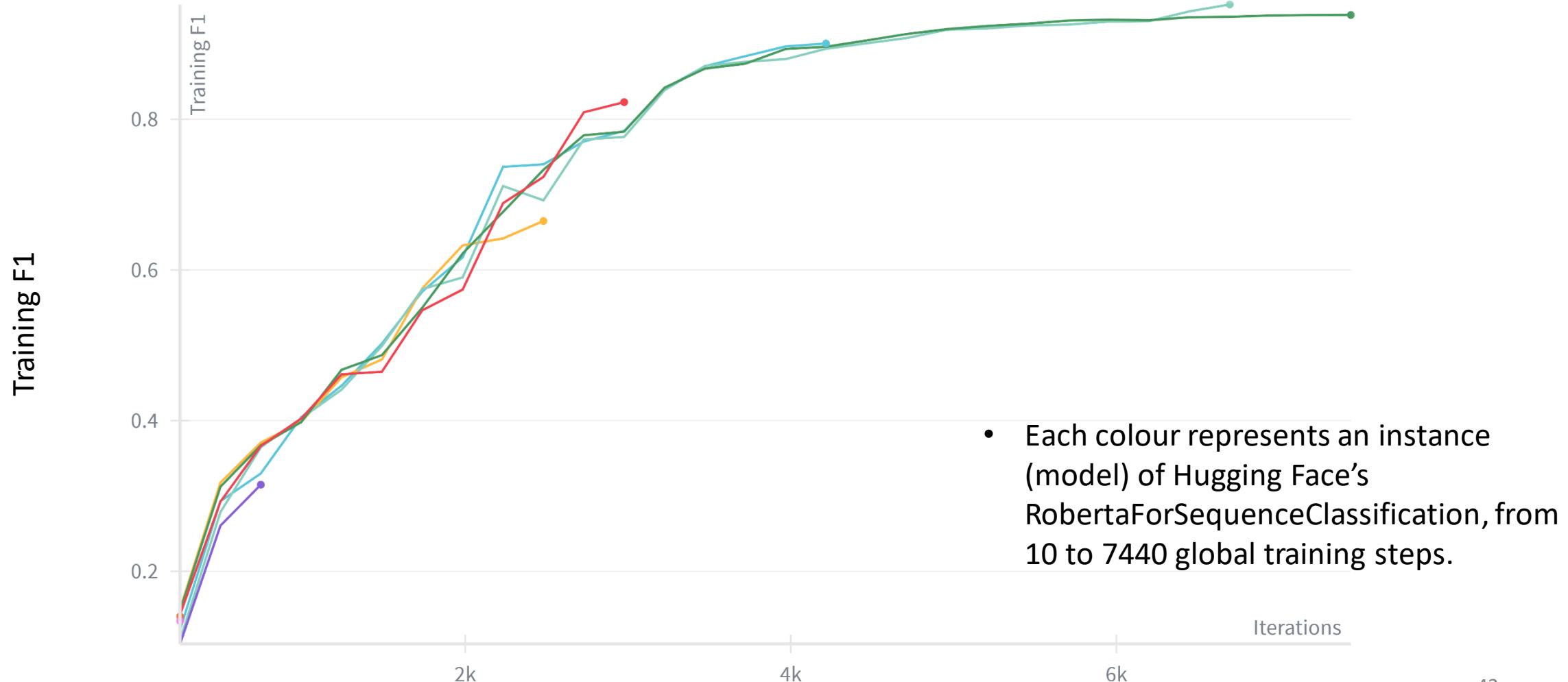


Experiment II, Classifier

- Each colour represents an instance (model) of Hugging Face's RobertaForSequenceClassification, from 10 to 7440 global training steps.

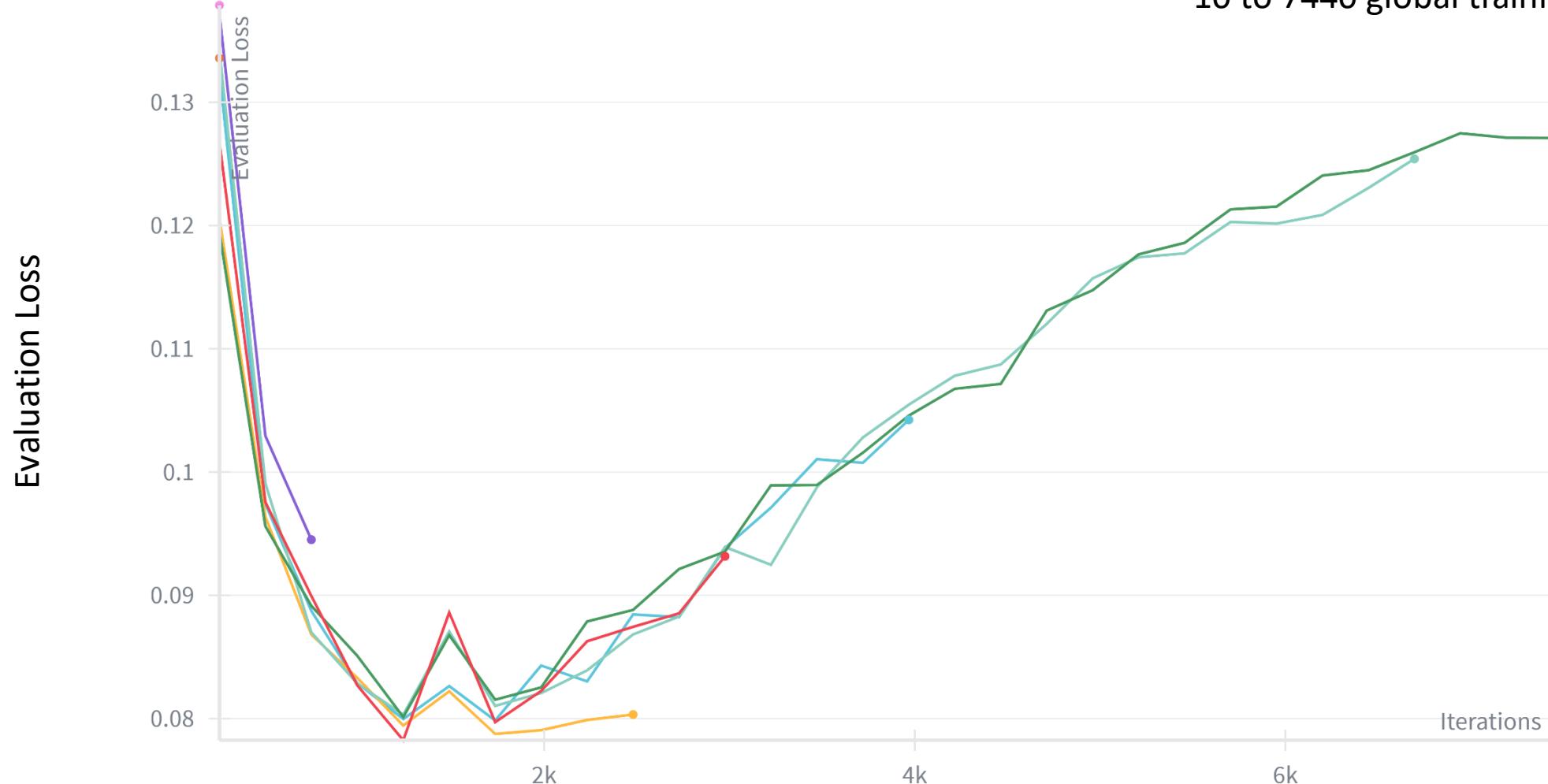


Experiment II, Classifier



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Experiment II, Classifier

