

# Item Response Theory for NLP

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<https://eacl2024irt.github.io/>

# Differences between Examples

## Natural language inference (NLI)

Premise	Hypothesis	Label	Difficulty
A little girl eating a sucker	A child eating candy	Entailment	<i>easy</i>
People were watching the tournament in the stadium	The people are sitting outside on the grass	Contradiction	<i>hard</i>
Two girls on a bridge dancing with the city skyline in the background	The girls are sisters.	Neutral	<i>easy</i>

## Sentiment analysis (SA)

Phrase	Label	Difficulty
The stupidest, most insulting movie of 2002's first quarter.	Negative	<i>easy</i>
Still, it gets the job done - a sleepy afternoon rental.	Negative	<i>hard</i>
An endlessly fascinating, landmark movie that is as bold as anything the cinema has seen in years.	Positive	<i>easy</i>
Perhaps no picture ever made has more literally showed that the road to hell is paved with good intentions.	Positive	<i>hard</i>

# Leaderboards

## 🤖 Open LLM Leaderboard

📌 The 🤖 Open LLM Leaderboard aims to track, rank and evaluate open LLMs and chatbots.

🤖 Submit a model for automated evaluation on the 🤖 GPU cluster on the "Submit" page! The leaderboard's backend runs the great [Eleuther AI Language Model Evaluation Harness](#) - read more details in the "About" page!

🏆 LLM Benchmark

📈 Metrics through time

📖 About

🚀 Submit here!

🔍 Search for your model (separate multiple queries with ';' and press ENTER...

Select columns to show

- ☒ Average 📊
- ☒ ARC
- ☒ HellaSwag
- ☒ MMLU
- ☒ TruthfulQA
- ☒ Winogrande
- ☒ GSM8K
- ☒ DROP
- ☐ Type
- ☐ Architecture
- ☐ Precision
- ☐ Hub License
- ☐ #Params (B)
- ☐ Hub ❤️
- ☐ Available on the hub
- ☐ Model sha

☐ Show gated/private/deleted models

Model types

- ☒ 🟢 pretrained
- ☒ 🟠 fine-tuned
- ☒ 🟡 instruction-tuned
- ☒ 🟦 RL-tuned
- ☒ ?

Precision

- ☒ float16
- ☒ bfloat16
- ☒ 8bit
- ☒ 4bit
- ☒ GPTQ
- ☒ ?

Model sizes (in billions of parameters)

- ☒ ?
- ☒ ~1.5
- ☒ ~3
- ☒ ~7
- ☒ ~13
- ☒ ~35
- ☒ ~60
- ☒ 70+

T	Model	Average 📊	ARC	HellaSwag	MMLU	TruthfulQA	Winogrande	GSM8K	DROP
🟠	<a href="#">TigerResearch/tigerbot-70b-chat-v2</a> 📄	69.76	87.03	82.83	66	75.4	79.16	46.02	51.9
🟡	<a href="#">bhenrym14/platypus-yi-34b</a> 📄	68.96	68.43	85.21	78.13	54.48	84.06	47.84	64.55
🟢	<a href="#">01-ai/Yi-34B</a> 📄	68.68	64.59	85.69	76.35	56.23	83.03	50.64	64.2
🟢	<a href="#">chargoddard/Yi-34B-Llama</a> 📄	68.4	64.59	85.63	76.31	55.6	82.79	49.51	64.37
🟡	<a href="#">MayaPH/Godzilla2-70B</a> 📄	67.01	71.42	87.53	69.88	61.54	83.19	43.21	52.31

[https://huggingface.co/spaces/HuggingFaceH4/open\\_llm\\_leaderboard](https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard)

# Differences in Questions

Compare Two Systems

Question



Burt

C

W

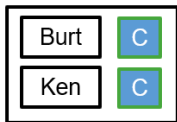


Ken

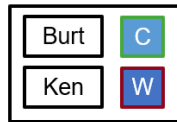
W

C

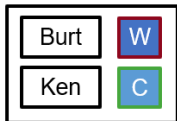
**Question:** Who did the Normans team up with in Anatolia?



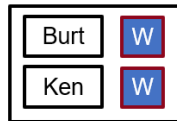
No Info



High Info



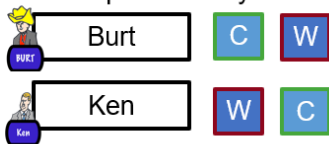
High Info



No Info

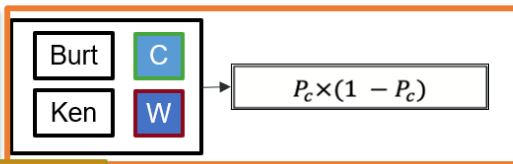
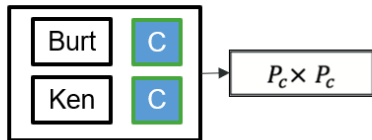
# Differences in Questions

## Compare Two Systems

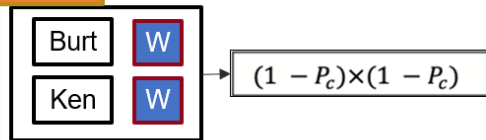
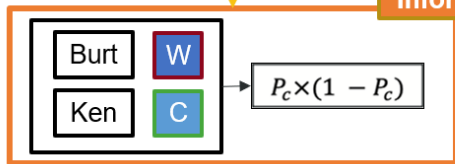


$P_c$  = Correct Probability,  $P_w$  = Wrong Probability

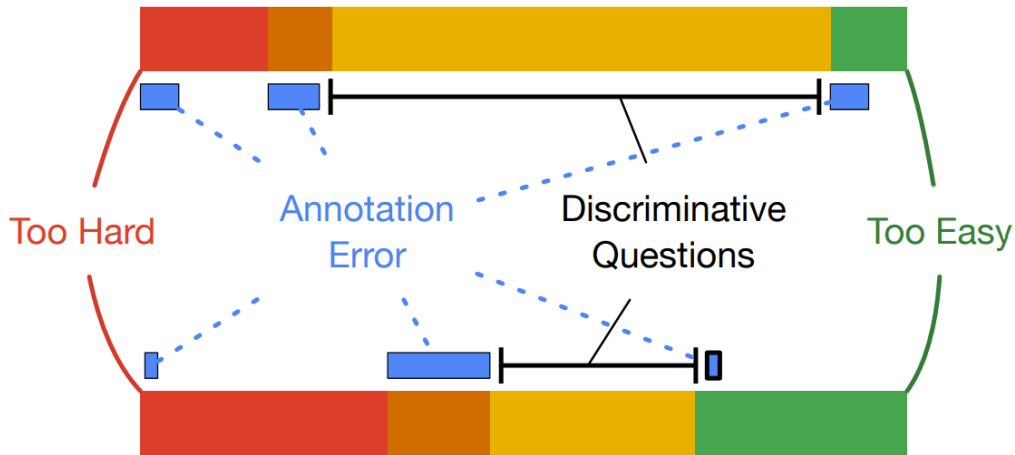
$$P_w = 1 - P_c$$



We're  
Informed Here



# Differences in Questions



# Psychometrics

Psychometrics: study of quantitative measurement practices

- Building instruments for measurement
- Development of theoretical approaches to measurement

Item Response Theory (IRT): measure latent traits of test-takers and test questions  
(“items’ ’)



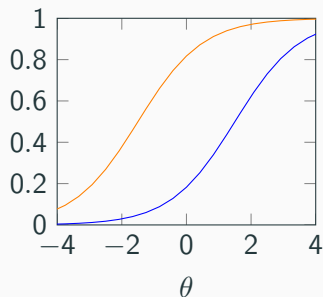
## IRT: 1 Parameter Logistic Model (1PL)

Also known as *Rasch model*

$$p(y_{ij} = 1 | b_i, \theta_j) = \frac{1}{1 + e^{-(\theta_j - b_i)}}$$

$\theta_j$ : latent ability

$b_i$ : difficulty





# Parameter Estimation

$$p(y_{ij} = 1|b_i, \theta_j) = \frac{1}{1 + e^{-a_i(\theta_j - b_i)}}$$

$$p(y_{ij} = 0|b_i, \theta_j) = 1 - p(y_{ij} = 1|b_i, \theta_j)$$

$$L = \prod_{j=1}^J \prod_{i=1}^I p(Y_{ij} = y_{ij}|b_i, \theta_j)$$

$$q(\Theta, B) = \prod_j \pi_j^\theta(\theta_j) \prod_i \pi_i^b(b_i)$$

## Evaluating DNN Performance with IRT

Premise	Hypothesis	Label	Difficulty
A little girl eating a sucker	A child eating candy	Entailment	-2.74
People were watching the tournament in the stadium	The people are sitting outside on the grass	Contradiction	0.51
Two girls on a bridge dancing with the city skyline in the background	The girls are sisters.	Neutral	-1.92
Nine men wearing tuxedos sing	Nine women wearing dresses sing	Contradiction	0.08

Phrase	Label	Difficulty
The stupidest, most insulting movie of 2002's first quarter.	Negative	-2.46
Still, it gets the job done - a sleepy afternoon rental.	Negative	1.78
An endlessly fascinating, landmark movie that is as bold as anything the cinema has seen in years.	Positive	-2.27
Perhaps no picture ever made has more literally showed that the road to hell is paved with good intentions.	Positive	2.05

## IRT for NLP: Human Annotations

Item Set	Theta Score	Percentile	Test Acc.
<b>5GS</b>			
Entailment	-0.133	44.83%	96.5%
Contradiction	1.539	93.82%	87.9%
Neutral	0.423	66.28%	88%
<b>4GS</b>			
Contradiction	1.777	96.25%	78.9%
Neutral	0.441	67%	83%

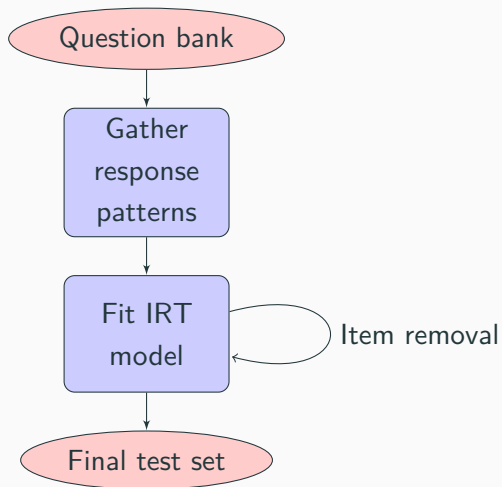
# Human Bottleneck

- Gathering human response patterns is expensive
- Can we use ensembles of models to gather response patterns?
- Even if we can, should we?

# Building IRT Models with Artificial Crowds

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## Building IRT Test Sets



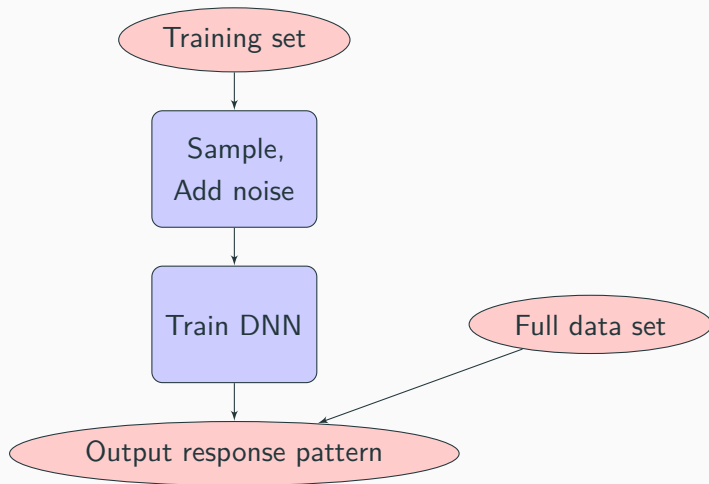
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# Artificial Crowd Construction

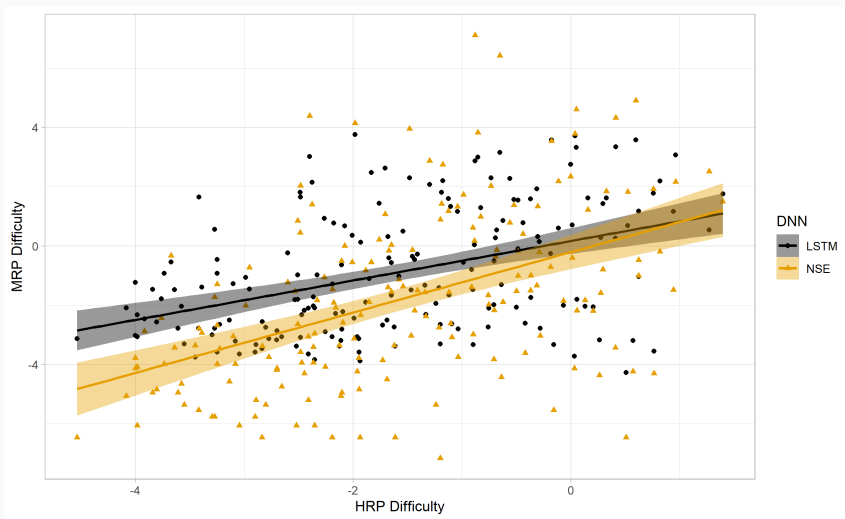




# Experiments

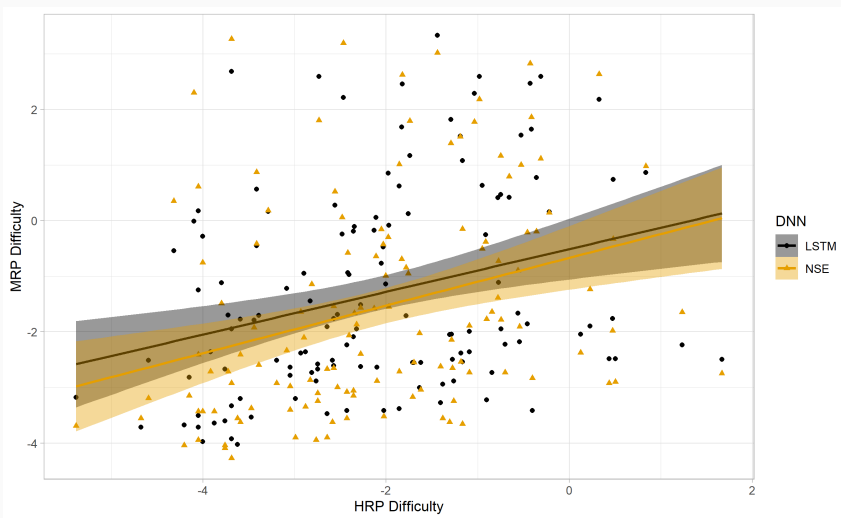
- Parameter comparison between models fit with human and machine response patterns
- Downstream use-case: training set filtering
- Qualitative evaluation: how do they look?

# Human-Machine Correlation



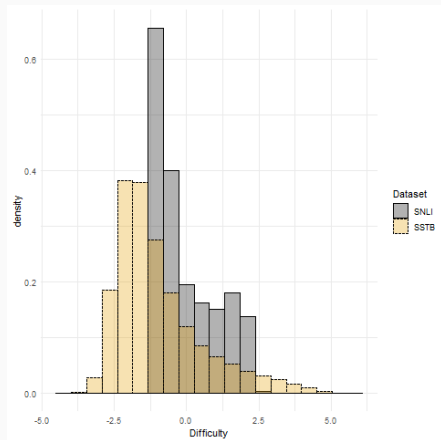
- Spearman  $\rho$  (NLI): 0.409 (LSTM) and 0.496 (NSE).

# Human-Machine Correlation



- Spearman  $\rho$  (SA): 0.332 (LSTM) and 0.392 (NSE).

# Difficulty Distribution



# IRT for Leaderboards (SQuAD)

System Developer



Runnable  
System



## What is SQuAD?

Stanford Question Answering Dataset (SQuAD) is a reading comprehension dataset, consisting of questions posed by crowdworkers on a set of Wikipedia articles, where the answer to every question is a segment of text, or span, from the corresponding reading passage, or the question might be unanswerable.

SQuAD 2.0 contains the 100,000 questions in SQuAD 1.1 with over 100,000 unanswerable questions written adversarially by crowdworkers to look similar to answerable ones. To do well on SQuAD 2.0, systems must not only answer questions when possible, but also determine when no answer is supported by the paragraph and abstain from answering.

Explore SQuAD 2.0 and model evaluation

SQuAD 2.0 Leaderboard & Kit v1.0

SQuAD 1.1, the previous version of the SQuAD dataset, contains 100,000 question-answer pairs on 100K articles.

Explore SQuAD 1.1 and model evaluation

SQuAD 1.1 Leaderboard & Kit v1.0

## Leaderboard

SQuAD 2.0 tests the ability of a system to not only answer reading comprehension questions, but also answer when presented with a question that cannot be answered based on the provided paragraph.

Rank	Model	EM	F1
	Human Performance	90.851	91.452
1	SA-Net on About (pretrained) (Gardner et al. 18)	90.724	91.811
2	SA-Net V2 (pretrained) (Gardner et al. 18)	90.679	91.748
3	Rein Reader (pretrained) (Singhal et al. 18)	90.678	91.876
4	ATNLP-P (pretrained) (Hosoi et al. 18)	90.462	91.877
5	ELECTRA-ALBERT-distilled (pretrained) (Joshi et al. 18)	90.442	91.829
6	ELECTRA-ALBERT-distilled (pretrained) (Joshi et al. 18)	90.420	91.799
7	ALBERT + DART + Reader (pretrained) (Pang et al. 18)	90.386	91.777

Dev Questions



Test Questions



Runnable System

Dev Predictions



Test Predictions



SQuAD Scoring Script

Dev Scores



Test Scores



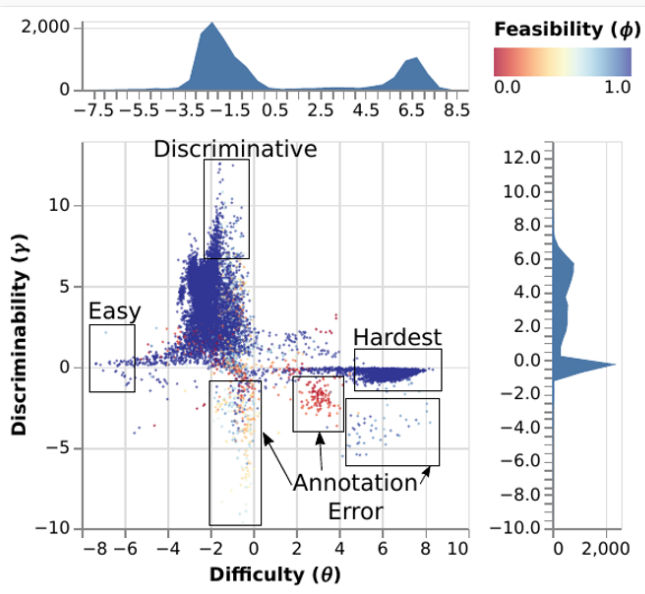
This is our data

66%

33%

- 1.9 million subject-item pairs

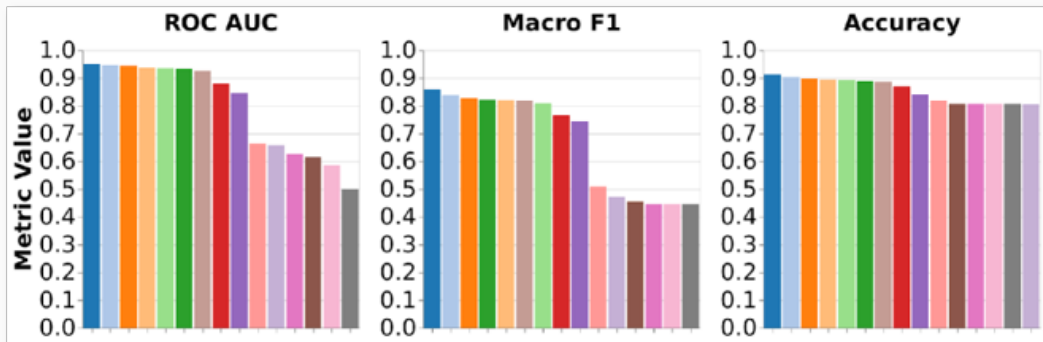
# IRT for SQuAD



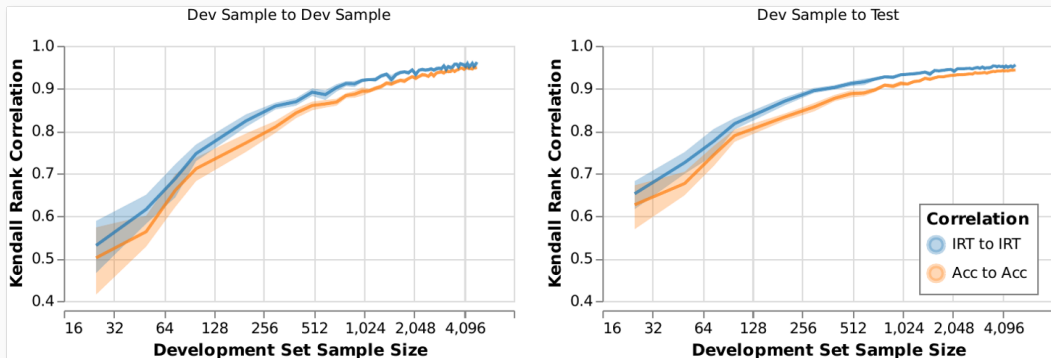
# Predicting Correct Responses

## Features

- |                |                    |
|----------------|--------------------|
| IRT-Vec        | LM +Question       |
| IRT-Feas       | LM +Context        |
| IRT-Disc       | LM +Stats          |
| IRT-Base       | LM +Subj & Item ID |
| LM All         | LM +Topics 1K      |
| LM +IRT        | LM +Title          |
| LM +Item ID    | LM +Baseline       |
| LM +Subject ID |                    |



# Ranking Performance





## IRT in Python: py-irt

```
{"subject_id": "pedro",    "responses": {"q1": 1, "q2": 0, "q3": 1, "q4": 0}}
{"subject_id": "pinguino", "responses": {"q1": 1, "q2": 1, "q3": 0, "q4": 0}}
{"subject_id": "ken",      "responses": {"q1": 1, "q2": 1, "q3": 1, "q4": 1}}
{"subject_id": "burt",     "responses": {"q1": 0, "q2": 0, "q3": 0, "q4": 0}}
```

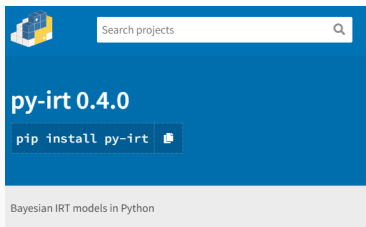
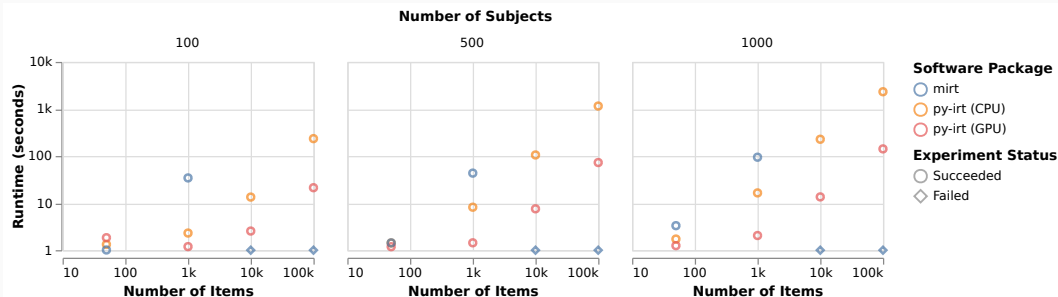
```
py-irt train 1pl data/data.jsonlines output/1pl/
```

```
{
  "ability": [
    -1.7251124382019043,
    -0.06789101660251617,
    1.6059941053390503,
    -0.20248053967952728
  ],
  "diff": [
    0.008014608174562454,
    9.654741287231445,
    -5.5452165603637695,
    -0.2792229950428009
  ],
  1,

```

```
"irt_model": "1pl",
"item_ids": {
  "0": "q2",
  "1": "q4",
  "2": "q1",
  "3": "q3"
},
"subject_ids": {
  "0": "burt",
  "1": "pinguino",
  "2": "ken",
  "3": "pedro"
}
}
```

# IRT in Python: py-irt



<https://github.com/nd-ball/py-irt>