Item Response Theory for NLP

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https://eacl2024irt.github.io/

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IRT for NLP

Overview of IRT Applications:

- Dataset Construction
- Model Training
- Evaluation

Assumptions for IRT + NLP

Basic assumptions of the data and parameterization we have:

- A dataset with items indexed by i.
- A set of subjects indexed by j.
- Responses r_{ij} from graded responses of subjects to each item.
- An IRT parameterization, e.g., one with item difficulty β_i, discriminability γ_i, and skill θ_j might assume:

$$p(r_{ij} = 1 | \beta_i, \theta_j) = \frac{1}{1 + e^{-\gamma_i(\theta_j - \beta_i)}}$$

What IRT Yields

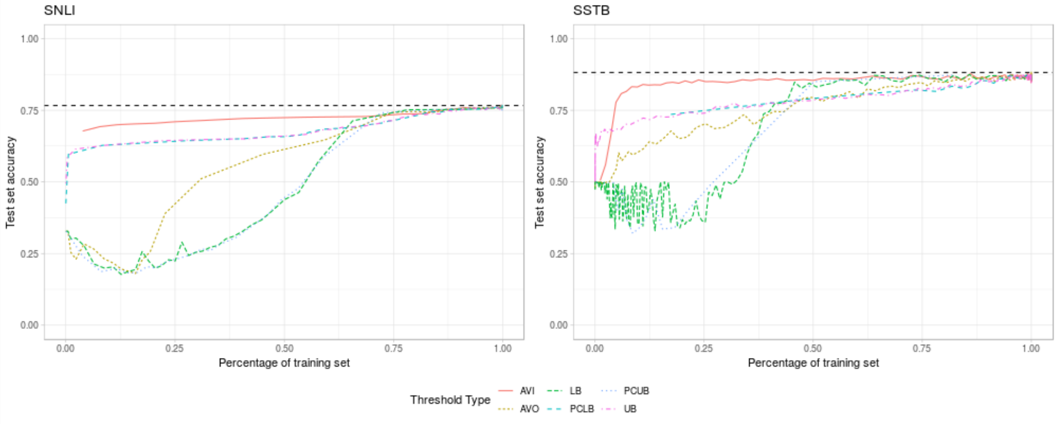
Given the previous information, IRT will yield estimates for chosen parameters, i.e.: item difficulty β_i, discriminability γ_i, and skill θ_j.

Consider two scenarios:

- What if the dataset is the training data?
- What if the dataset is a test set?

Improving Model Training

Data set filtering



- AVI: $|b_i| < \tau$
- UB: $b_i < \tau$
- PCUB: $pc_i < \tau$
- AVO: $|b_i| > \tau$
- LB: $b_i > \tau$
- PCLB: $pc_i > \tau$

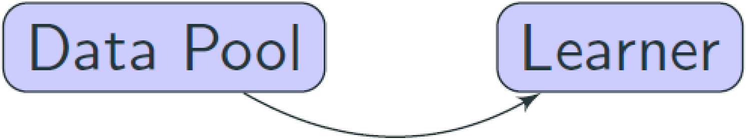
MT-DNN Results

Strategy	% of Training Data		
	0.1%	1%	10%
Random (reported)	82.1	85.2	**88.4**
Random (small batch)	81.79	84.90	88.32
Lower-bound	43.68	41.56	39.89
Upper-bound	81.62	80.46	79.06
AVI	**82.44**	**85.44**	86.73
AVO	43.60	42.05	40.81

Biggest Differences

Task	Label	Item Text	Difficulty ranking		
			Humans	LSTM	NSE
SNLI	Con.	*P:* Two dogs playing in snow. *H:* A cat sleeps on floor	168	1	5
	Ent.	*P:* A girl in a newspaper hat with a bow is unwrapping an item. *H:* The girl is going to find out what is under the wrapping paper.	55	172	176
SSTB	Pos.	Only two words will tell you what you know when deciding to see it: Anthony. Hopkins.	9	103	110
	Neg.	...are of course stultifyingly contrived and too stylized by half. Still, it gets the job done–a sleepy afternoon rental.	128	46	41

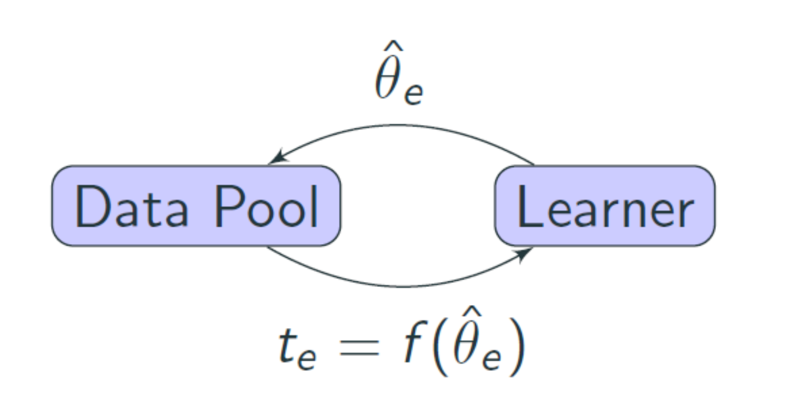
Traditional Curriculum Learning



$$t_e = f(e)$$

- Example difficulty based on heuristics
    - Replace heuristic with IRT difficulty
- Strategy is static
- Competence-based CL: $t_e = f(e, c_0)$ (Platanios et al., 2019)

Dynamic Data Selection



- Example difficulty is learned
- Training set *dynamically selected* as a function of model ability

Estimating θ

Gather responses from model j for items with known difficulties

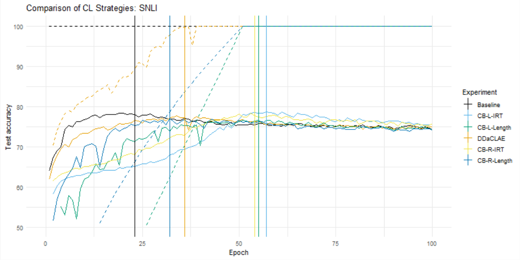
$$
\begin{aligned}
Z_j &= \forall_{y \in Y} \mathbf{I}[y_i = \hat{y}_i] \\
L(\theta_j | Z_j) &= p(Z_j | \theta_j) \\
\hat{\theta}_j &= \arg\max_{\theta_j} \prod_{i=1}^{I} p(z_{ij} = y_{ij} | \theta_j)
\end{aligned}
$$

DDaCLAE

Dynamic Data selection for Curriculum Learning via Ability Estimation

- At each epoch e:
  - Label all data: $\hat{Y}$
  - Estimate $\hat{\theta}_e$: $score(Y, \hat{Y}, B)$
  - Select training data: $b_i \leq \hat{\theta}_e$

Results



(a) SNLI

(b) SSTB

Results

Metric	Experiment	MNIST	CIFAR	SSTB	SNLI
%Δ	Baseline	0	0	0	**0**
Train Size	DDaCLAE	**-9.37**	**-53.71**	**-88.68**	33.51
	CB Lin	-8.22	-21.56	-73.17	38.07
	CB Root	11.29	-22.63	10.23	60.08
%Δ	Baseline	**0**	0	0	0
Accuracy	DDaCLAE	-0.17	**0.66**	**0.45**	-1.08
	CB Lin	-0.01	-0.90	-0.18	**0.69**
	CB Root	-0.06	0.13	-0.38	-0.37

Results

Label	Review	Δ_d
Pos	Heart	67342
Pos	The year's greatest adventure, and Jackson's limited but enthusiastic adaptation has made literature literal without killing its soul – a feat any thinking person is bound to appreciate.	67334
Pos	Hip	67332
Neg	Exit	67346
Neg	There's an admirable rigor to Jimmy's relentless anger, and to the script's refusal of a happy ending, but as those monologues stretch on and on, you realize there's no place for this story to go but down.	67330

Results

Label	Premise	Hypothesis	Δ_d
Con.	Two men in a jogging race on a black top street, one man wearing a black top and pants and the other is dressed as a nun with bright red tennis shoes, while onlookers stand in a grassy area and watch from behind a waist high metal railing.	There is no metal railing.	549179
Ent.	Two dogs in the water.	They are swimming	549180
Neut.	Male musicians are playing a gig with one on the drums and the other on the guitar, with a backdrop of purple graphics apart of the light show.	Male musicians with long hair are playing a gig with one on the drums and the other on the guitar, with a backdrop of purple graphics apart of the light show.	549184
Neut.	A dog in a lake.	A dog is swimming.	549183

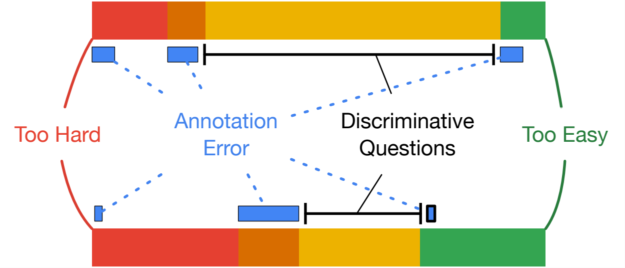
Remarks

- Correlation between parameters between human and machine IRT models
- Downstream effectiveness of difficulty
- Qualitative check of learned parameters
- What about θ?

Finding Annotation Error

IRT Applications: Finding Annotation Error

Test examples can be: too hard, discriminative, too easy, or erroneous [1]



How can we use IRT to identify each example type?

[1] Boyd-Graber and Börschinger (2020)

IRT Applications: Finding Annotation Error

What makes examples bad?

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- What parameter could identify this?

IRT Applications: Finding Annotation Error

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- Examples that do not discriminate between good and bad subjects
- Example: Bad label $\rightarrow$ all models get wrong
- Example: Correctness is a coinflip
- Non-Example: Difficult example few models get correct
- What parameter could identify this?
- We can use IRT discriminability γ_i to find bad examples!

IRT Applications: Setup for Finding Annotation Error

Can follow along in notebook! Setup/Assumptions:

- Run a simulation where:

Then, train a 3PL IRT model with py-irt

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- Run a simulation where:
- 10 Subjects, Skill $\sim U(-4, 4)$

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IRT Applications: Setup for Finding Annotation Error

Can follow along in notebook! Setup/Assumptions:

- Run a simulation where:
- 10 Subjects, Skill $\sim U(-4, 4)$
- 1000 Items, Difficulty $\sim U(-4, 4)$

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- Run a simulation where:
- 10 Subjects, Skill $\sim U(-4, 4)$
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- Items have a 5% of being invalid

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- Items have a 5% of being invalid
- Responses for valid items: $r_{ij} = sigmoid(\theta_j - \beta_i) > u, u \sim U(0, 1)$
- Responses for invalid items: $r_{ij} = u > .5, u \sim U(0, 1)$

Then, train a 3PL IRT model with py-irt

IRT Applications: Setup for Finding Annotation Error

IRT Parameters

- Item Difficulty: $\beta_i \sim$ Normal
- Item Discriminability: $\gamma_i \sim$ LogNormal
- Subject Skill $\theta_j \sim$ Normal

IRT Model

$$p(r_{ij} = 1 | \beta_i, \gamma_i, \theta_j) = \frac{1}{1 + e^{-\gamma_i(\theta_j - \beta_i)}}$$

IRT Applications: Setup for Finding Annotation Error

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$$p(r_{ij} = 1 | \beta_i, \gamma_i, \theta_j) = \frac{1}{1 + e^{-\gamma_i(\theta_j - \beta_i)}}$$

Note:

- Why $\gamma_i \sim$ LogNormal? Following Vania et al. (2021), forces γ_i to be non-negative.
- Other variables are zero centered.

IRT Applications: Sample Code for Finding Errors

Sample Code

```
dataset = Dataset.from_jsonlines(”/tmp/irt_dataset.jsonlines”)
config = IrtConfig(
  model_type='tutorial', log_every=500, dropout=.2
)
trainer = IrtModelTrainer(
  config=config, data_path=None, dataset=dataset
)
trainer.train(epochs=5000, device='cuda')
```

IRT Applications: Simulation Results

Can we distinguish valid from invalid items based on discriminability γ_i?

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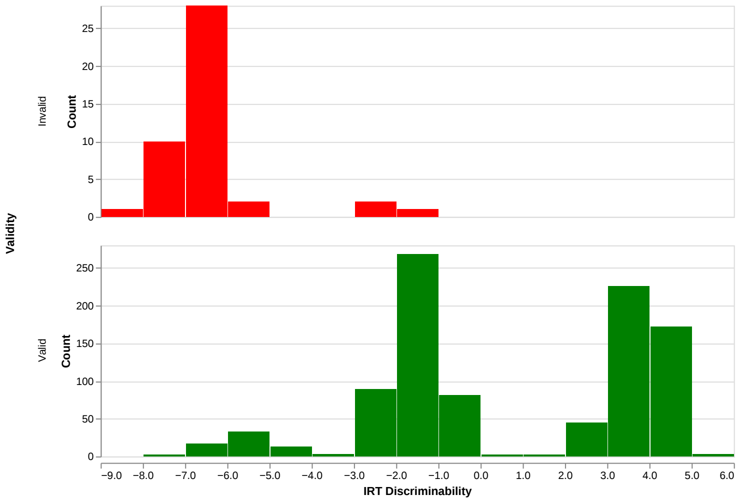
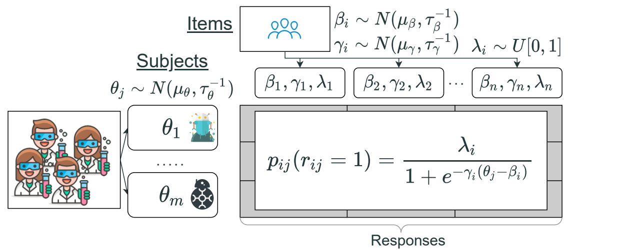


IRT Applications: Finding Annotation Error

In Rodriguez et al. (2021), we used a slightly different model to do this for SQuAD:

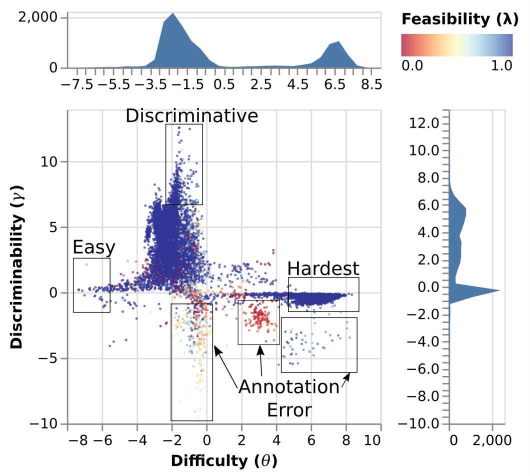


Differences

- Discriminability γ_i could be negative, which is inconvenient
- Feasibility λ_i more difficult to control

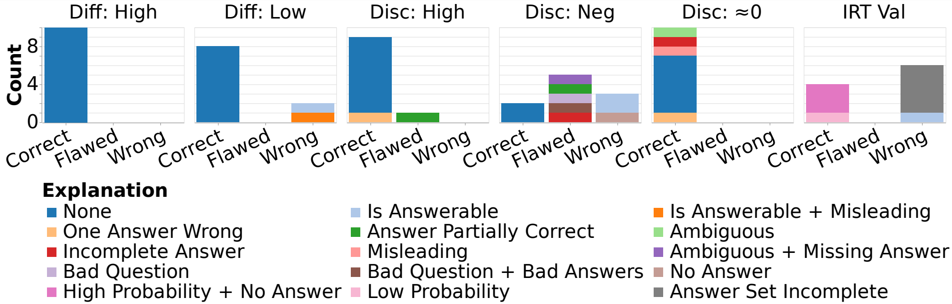
IRT Applications: Finding Annotation Error

Plotting IRT parameters:



IRT Applications: Finding Annotation Error

Use IRT parameters to find partitions of data with annotation errors



Things to note:

- Difficulty can be high or low, not an issue itself
- Negative discriminability identifies errors

Evaluation Metrics

IRT Applications: Evaluation Metrics

Simple Idea: Instead of accuracy, use subject skill θ_j to rank.

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What are the tradeoffs?

IRT Applications: Evaluation Metrics Example

Suppose the following:

- As before, 1,000 Test Examples
- A set of 800 easy examples
- A set of 150 moderate examples
- A set of 50 hard examples
- 10 Subjects, similar setup as before

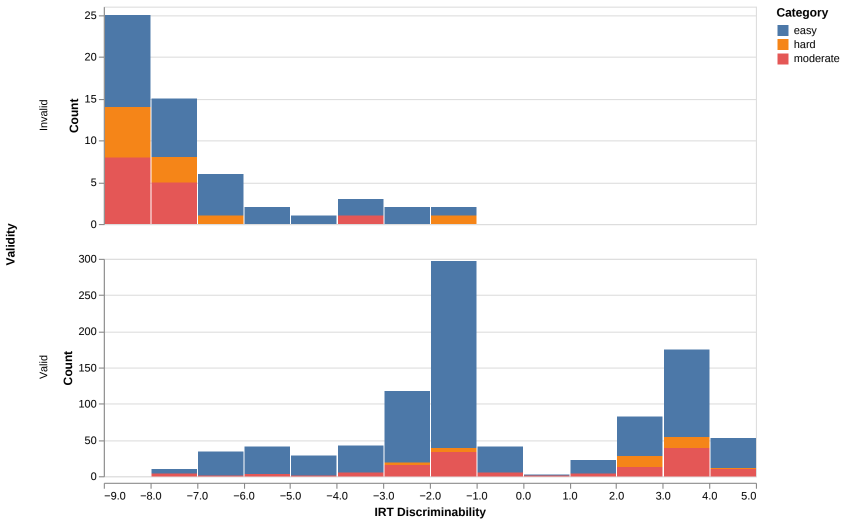
IRT Applications: Evaluation Metrics Example

- Subjects sorted by True skill
- Accuracy gaps vary
- IRT can account for some of this variability

True	IRT	Total	Easy	Mod	Hard
-3.506	-12.1	0.194	0.218	0.093	0.100
-3.000	-7.61	0.256	0.301	0.066	0.100
-2.645	-4.88	0.325	0.380	0.093	0.140
-1.214	0.348	0.543	0.650	0.113	0.120
-1.156	1.40	0.560	0.667	0.120	0.160
-0.748	2.68	0.602	0.712	0.146	0.200
-0.455	3.36	0.631	0.746	0.193	0.100
0.232	5.76	0.729	0.848	0.293	0.120
2.16	11.1	0.865	0.956	0.586	0.240
2.50	14.2	0.897	0.971	0.686	0.340

IRT Applications: Discounting Bad Examples

- Invalid examples sorted down
- Harder examples tend to be more discriminating



IRT Applications: Rank Reliability in Evaluation Metrics

In Rodriguez et al. (2021), we examined a case like the SAT where we have:

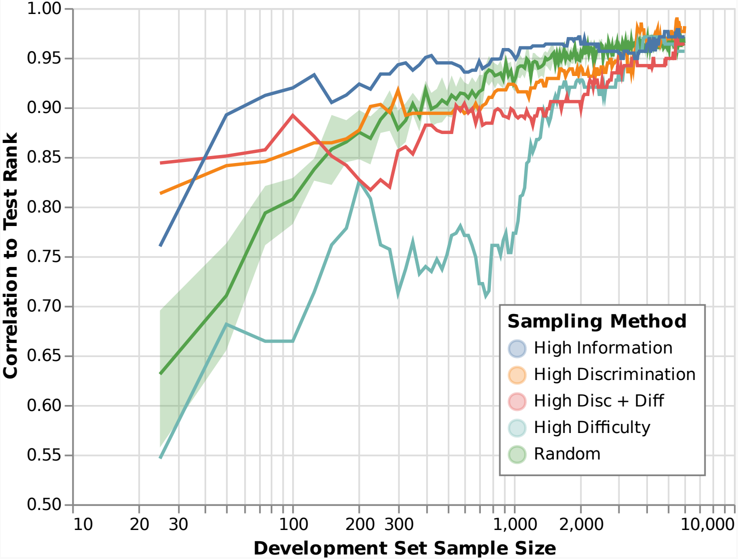
- Pre-existing set of annotated responses for subjects/items
- Have a set of subjects (i.e., new models), same items.
- We want to minimize the number of subject responses to annotate, while maximizing the reliability of the resulting ranking.
- Baseline: Random sample
- IRT Methods: Sample based on different parameters

IRT Applications: Rank Reliability in Evaluation Metrics

Overall best method: pick item that maximizes Fisher information content, i.e.,

$$I_i(\theta_j) = \gamma_i^2 p_{ij}(1 - p_{ij})$$

$$Info(i) = \sum_j I_i(\theta_j)$$



Additional Work

- Alternate Evaluation Metrics, e.g., Subject skill θ_j (Lalor et al., 2018)
- Estimate Longevity of Tasks (Vania et al., 2021)
- Efficient Test Set Selection (non-irt) (Vivek et al., 2024)
- Building Tiny Benchmarks (Polo et al., 2024)

References

Jordan Boyd-Graber and Benjamin Börschinger. 2020. What question answering can learn from trivia nerds. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7422–7435, Online. Association for Computational Linguistics.

John P. Lalor, Hao Wu, Tsendsuren Munkhdalai, and Hong Yu. 2018. Understanding deep learning performance through an examination of test set difficulty: A psychometric case study. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4711–4716, Brussels, Belgium. Association for Computational Linguistics.

John P. Lalor, Hao Wu, and Hong Yu. 2019. Learning latent parameters without human response patterns: Item response theory with artificial crowds. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 4249–4259, Hong Kong, China. Association for Computational Linguistics.

John P. Lalor and Hong Yu. 2020. Dynamic data selection for curriculum learning via ability estimation. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 545–555, Online. Association for Computational Linguistics.

Emmanouil Antonios Platanios, Otilia Stretcu, Graham Neubig, Barnabas Poczos, and Tom Mitchell. 2019. Competence-based curriculum learning for neural machine translation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1162–1172, Minneapolis, Minnesota. Association for Computational Linguistics.

Felipe Maia Polo, Lucas Weber, Leshem Choshen, Yuekai Sun, Gongjun Xu, and Mikhail Yurochkin. 2024. tinybenchmarks: evaluating llms with fewer examples.

Pedro Rodriguez, Joe Barrow, Alexander Miserlis Hoyle, John P. Lalor, Robin Jia, and Jordan Boyd-Graber. 2021. Evaluation examples are not equally informative: How should that change NLP leaderboards? In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4486–4503, Online. Association for Computational Linguistics.

Clara Vania, Phu Mon Htut, William Huang, Dhara Mungra, Richard Yuanzhe Pang, Jason Phang, Haokun Liu, Kyunghyun Cho, and Samuel R. Bowman. 2021. Comparing test sets with item response theory. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1141–1158, Online. Association for Computational Linguistics.

Rajan Vivek, Kawin Ethayarajh, Diyi Yang, and Douwe Kiela. 2024. Anchor points: Benchmarking models with much fewer examples. In *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1576–1601, St. Julian's, Malta. Association for Computational Linguistics.