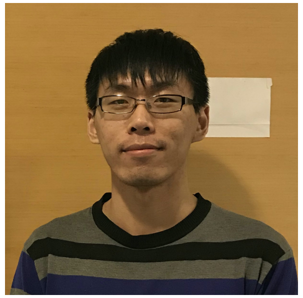
How Can We Know
What and **When** Language Models Know?

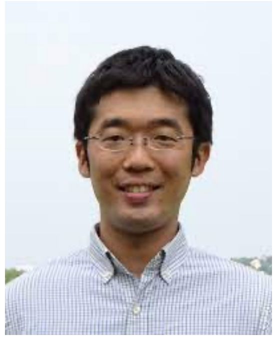
Graham Neubig

Carnegie Mellon University
School of Computer Science

NEULAB

Based on research w/
Zhengbao Jiang, Frank F. Xu, Haibo Ding, and Jun Araki



+ Bonus?!: Interpretable Evaluation + ExplainaBoard

Language Modeling

- Predict the likelihood of a sentence P(X)

Barack Obama served as the 44^{th} President of the United States.	P(X) is high	
44^{th} the of the President United States served Barack Obama as.	P(X) is low	syntax
Barack Obama barked as the 44^{th} President of the kennel.	P(X) is low	semantics
Barack Obama served as the 42^{nd} President of the United States.	P(X) is low	facts
Barack Obama reached a height of 50 feet tall.	P(X) is low	common sense

Prompting LMs for Knowledge

Factual Question Answering

Tokyo is the capital of [MASK].

Mask 1 Predictions:

96.1%	Japan
1.6%	Asia
1.0%	Tokyo
0.2%	Korea
0.2%	India

Petroni et al. (2019)

Text Classification

I loved this movie. The movie was [MASK].

{bad, OK, good}

Yin et al. (2019)

In Dialogue Context

Human: Hi!
Meena: Hi there! How's it going?
Human: Pretty well.
Meena: I'm glad to hear it. :D
Human: What is your favorite book?
Meena: Oh, that's a toughie. Right now I'd have to say it's A Dance With Dragons, but Harry Potter is a close second.
Human: Oh I love Harry Potter
Meena: Me too! I've read the series at least five times over.
Human: Haha, same probably. Which one do you like the most
Meena: Probably Chamber of Secrets.
…

Example from Meena chatbot (Adiwardana et al. 2020)
https://github.com/google-research/google-research/blob/master/meena/meena.txt

Prompting Difficulties

- LMs were **never trained** to solve the exact tasks that we're asking them to solve
- Because of this, they are
  - **Very sensitive to the wording** that we use to prompt them
  - Will return an answer **even when they have no idea**
- In this talk we ask:
  - How can we know **what** language models know through better **prompting**?
  - How can we know **when** language models know through better **calibration**?

How Can We Know What Language Models Know?

Zhengbao Jiang, Frank F. Xu, Jun Araki, Graham Neubig

TACL 2020

Paper: https://arxiv.org/pdf/1911.12543.pdf

Code: https://github.com/jzbjyb/LPAQA

Sub-optimal Prompts (in Factual Probing)

DirectX is developed by [MASK]. | [MASK] released the DirectX. | DirectX is created by [MASK].

1	Intel	-1.06	Microsoft	-1.77	Microsoft	-2.23
2	Microsoft	-2.21	They	-2.43	Intel	-2.30
3	IBM	-2.76	It	-2.80	default	-2.96
4	Google	-3.40	Sega	-3.01	Apple	-3.44
5	Nokia	-3.58	Sony	-3.19	Google	-3.45

Inappropriate prompts might fail to retrieve facts that the LM *does* know

How can we most effectively probe language models?

Motivations

- Any given prompt only provides a lower bound estimate.
- Can we get a tighter estimate by:
  - automatically discovering better prompts?
  - combining a diverse set of prompts?

Answer: Yes! Careful prompt design leads to up to 8.5% increase in fact retrieval accuracy.

Prompt Generation

- **Mining-based**
  - Middle-word

    Barack Obama was born in Hawaii. → [X] was born in [Y].
  - Dependency-based

    The capital of France is Paris. → capital of [X] is [Y].

- **Paraphrasing-based**

  Back translation with beam search

[X] shares a border with [Y]. → en-de model → de-en model → [X] has a common border with [Y]. [X] adjoins [Y]. ……

Prompt Ensembling

$$s([\mathrm{Y}]|[\mathrm{X}], \mathrm{owned\_by}) = \sum_{i=1}^{3} w_i * \log P_{\mathrm{LM}}([\mathrm{Y}]|[\mathrm{X}], t_i)$$

.485

.151.

.151.

[X] is owned by [Y].

[X] was acquired by [Y].

[X] division of [Y].

Experimental settings

- Datasets
  - LAMA
    46 relations from Wikidata, each associated with 1000 subject-object (X-Y) pairs.
  - LAMA-UHN
    - A difficult subset of facts from LAMA.
  - Google-RE
    - 3 relations.

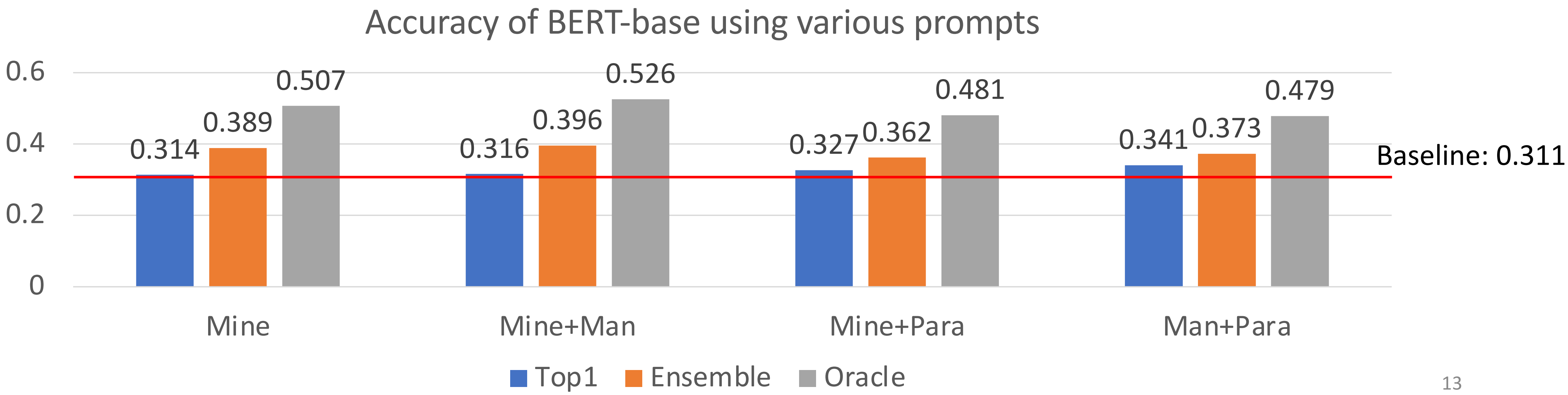
Relations	Subject-object pairs
[X] was born in [Y] .	(Allan Peiper, Alexandra), (Paul Mounsey, Scotland), …
[X] plays in [Y] position .	(Johan Santana, pitcher), (Koke, midfielder), …
[X] is developed by [Y] .	(MessagePad, Apple), (Adobe Illustrator Artwork, Adobe), …

Experimental settings

- Dataset: LAMA, a dataset of relations from a knowledge base
- Methods
  - Prompts
    - **Man:** manually created prompts.
    - **Mine:** mining-based prompts from Wikipedia articles.
    - **Para:** paraphrasing-based prompts from WMT'19 English-German models.
  - Ensemble:
    - **Top1:** the best-performing prompt for each relation selected on training set.
    - **Ensemble:** combine 40 prompts by weights learned on training set.
    - **Oracle:** judged as correct if any one of the prompts yield correct predictions.
- Metrics
  - Accuracy: accuracy average across relations.

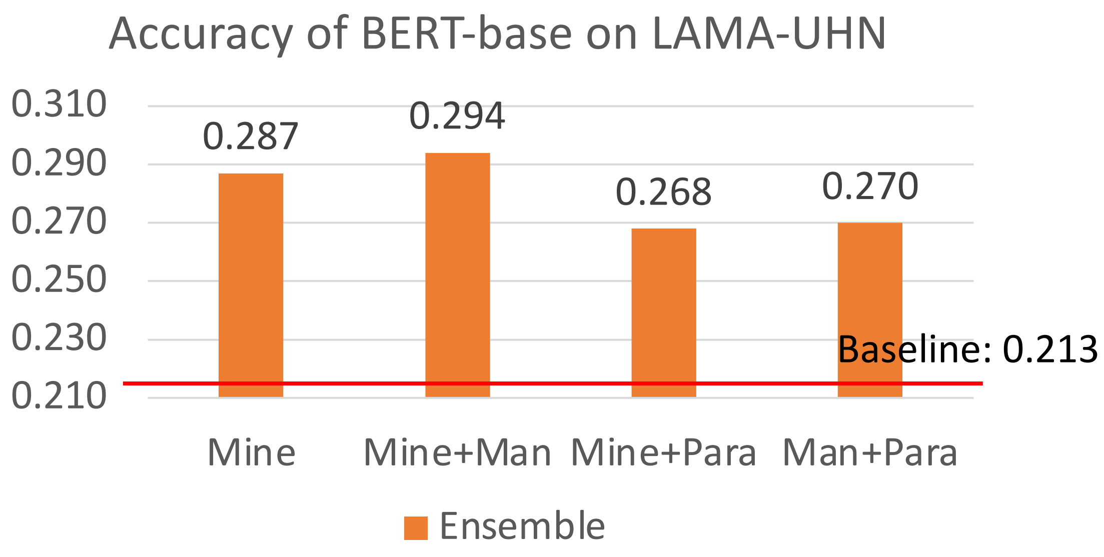
Results

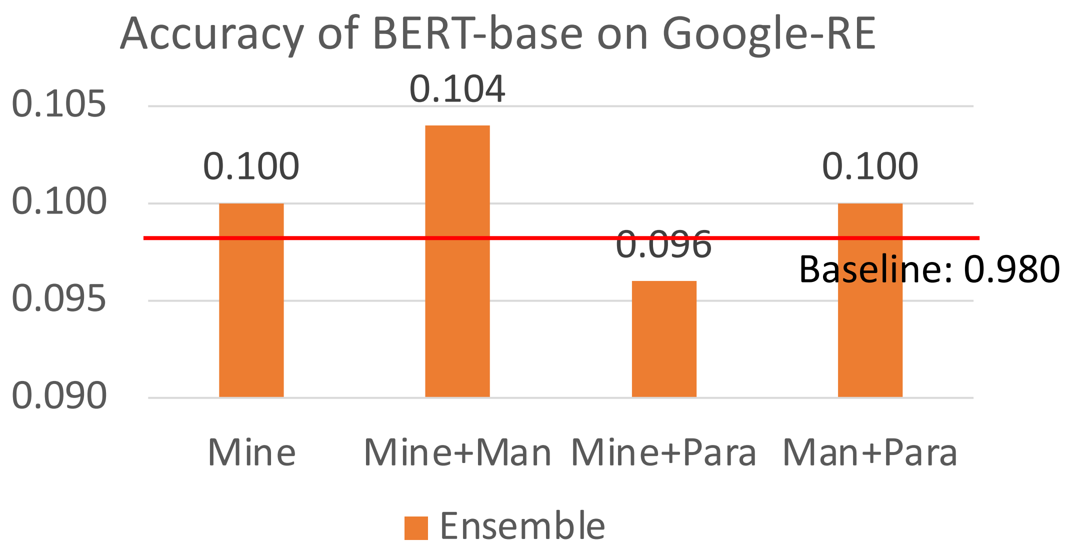
- Top1 > Baseline (Man): **automatic prompts provide better accuracy**.
- Ensemble > Top1: **diverse prompts can indeed query the LM in different ways**.
- Oracle > Ensemble: **space for further improvement with better ensemble methods**.



Results on LAMA-UHN and Google-RE

- Ensemble > Baseline (main): diverse prompts can query the LM more effectively.





Case study

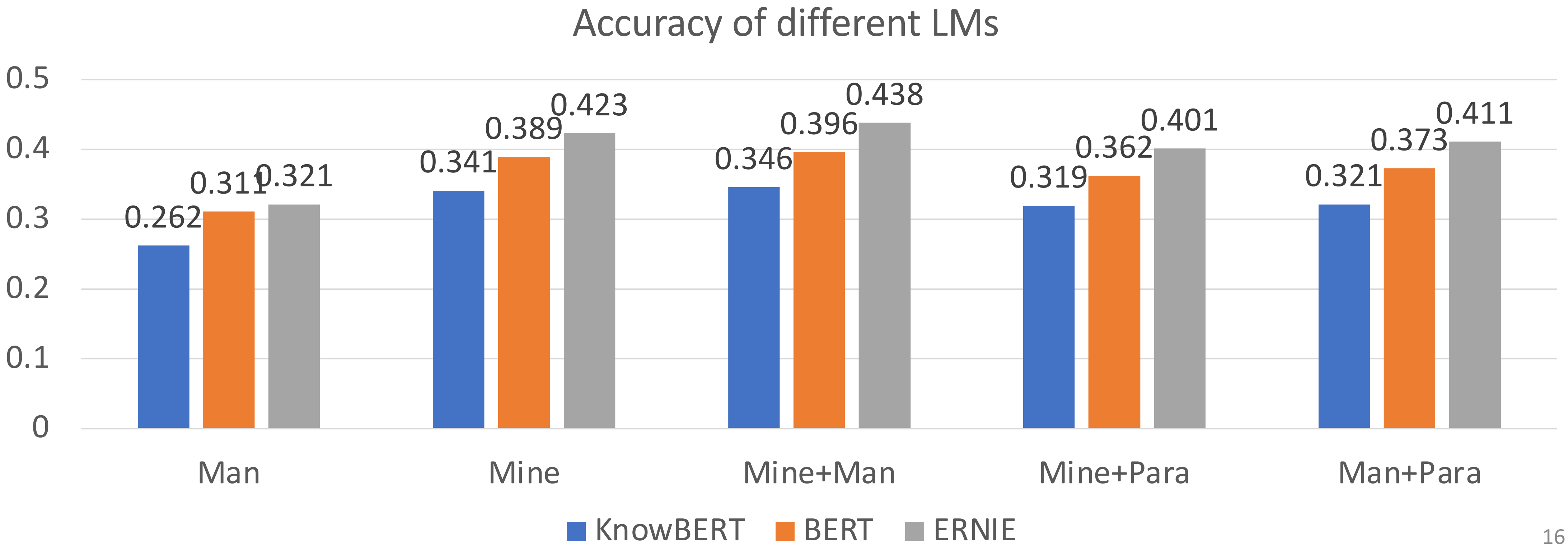
Manual prompts	Generated prompts	
[X] is affiliated with the [Y] religion.	[X] who converted to [Y].	+60%
[X] is represented by music label [Y].	[X] recorded for [Y].	+17%

Simple edits

[X] plays in→at [Y] position	+23%
[X] was created→made in [Y]	+11%

Results of different LMs

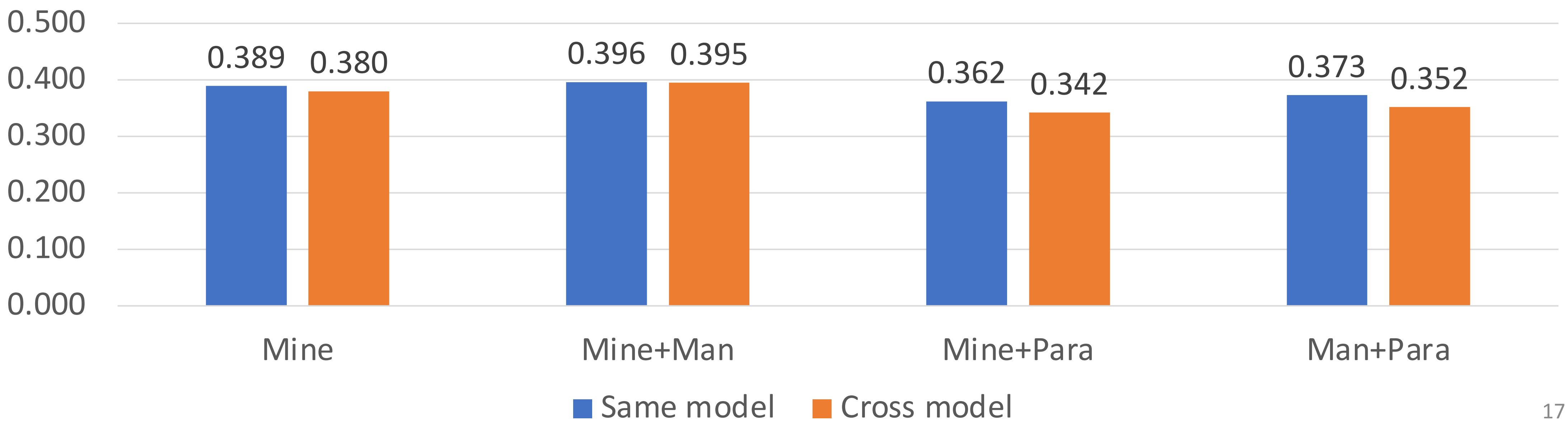
- KnowBERT < BERT < ERNIE



Cross-model consistency

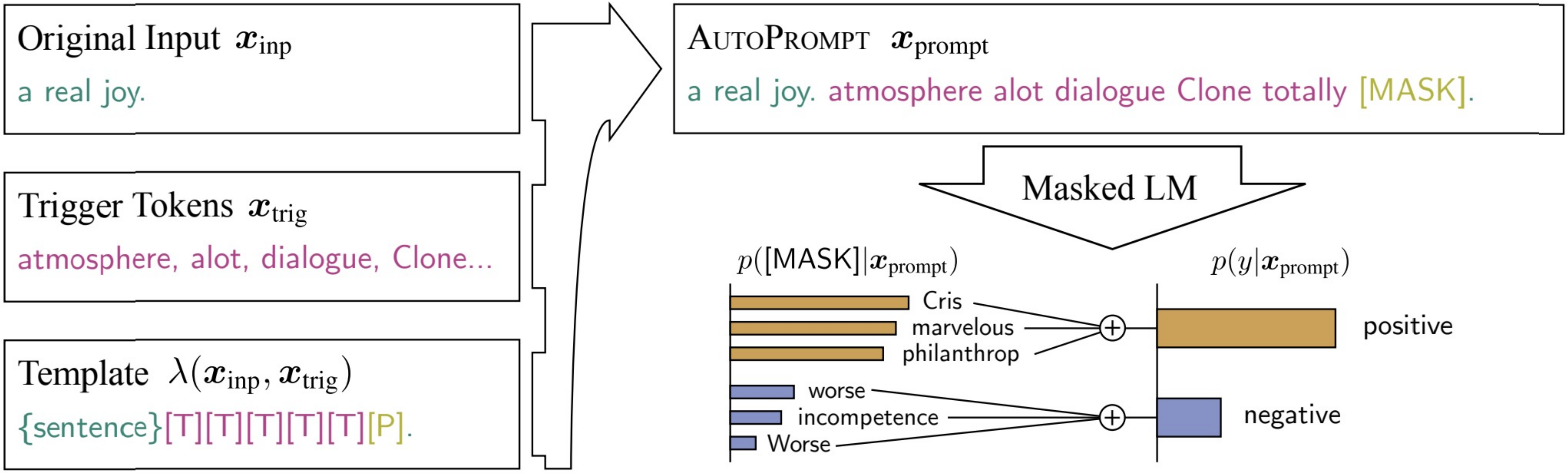
Ensemble weights are consistent across models

- Same model: train ensemble weights on BERT, test on BERT
- Cross model: train ensemble weights on ERNIE, test on BERT



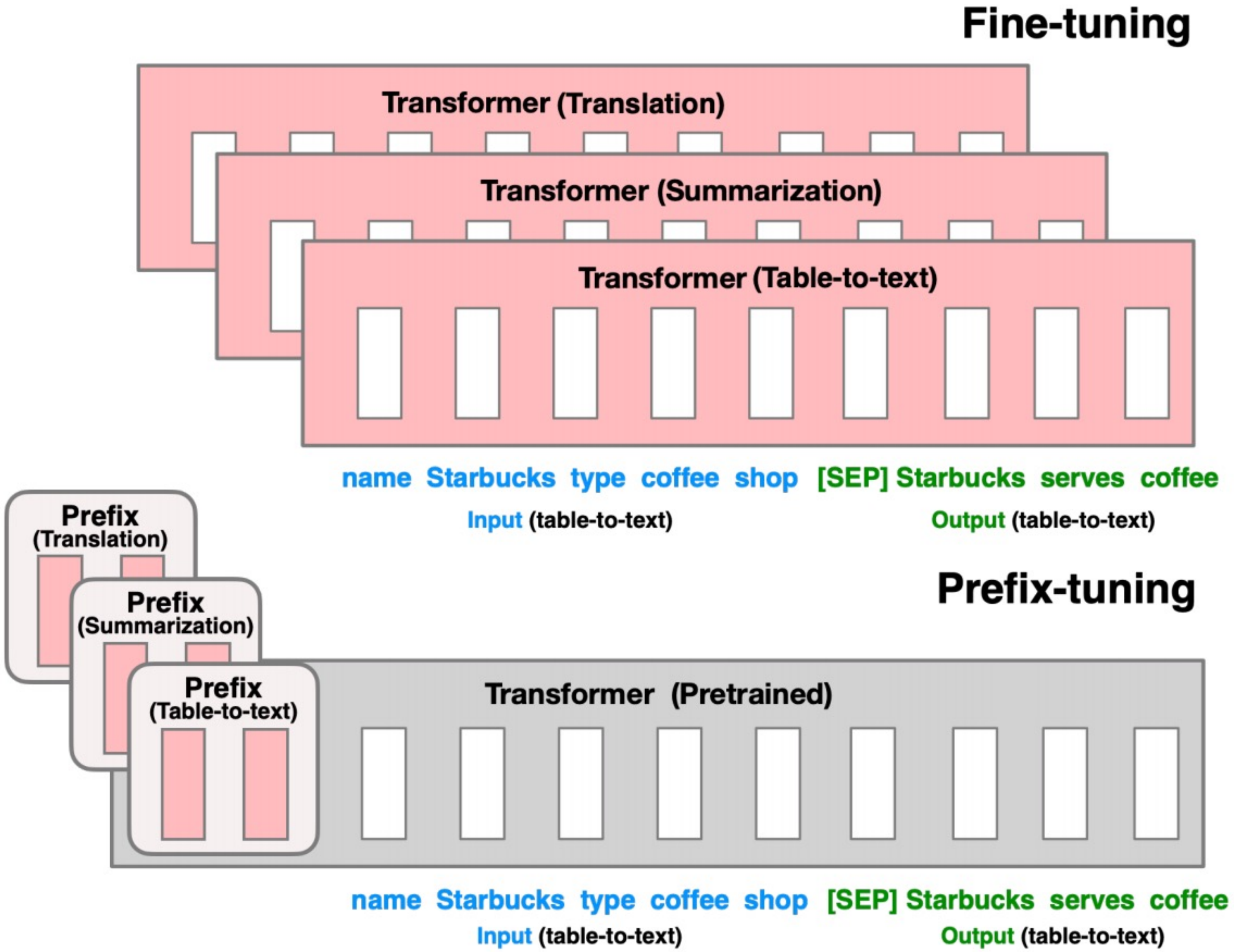
Follow-up: AutoPrompt (Shin et al. 2020)

- Automatically optimize arbitrary prompts based on existing words



Follow-up: Prefix Tuning (Li and Liang 2021)

- Optimize the embeddings of a prompt, instead of the words.



How Can We Know When LMs Know? On the Calibration of Language Models for Question Answering

Zhengbao Jiang, Jun Araki, Haibo Ding , Graham Neubig

TACL 2021

Paper: https://arxiv.org/abs/2012.00955

LMs are not omnipotent

- Fail to provide appropriate answers in many cases

```
Q: How many eyes does a giraffe have?
A: A giraffe has two eyes.

Q: How many eyes does my foot have?
A: Your foot has two eyes.

Q: How many eyes does a spider have?
A: A spider has eight eyes.

Q: How many eyes does the sun have?
A: The sun has one eye.

Q: How many eyes does a blade of grass have?
A: A blade of grass has one eye.
```

https://lacker.io/ai/2020/07/06/giving-gpt-3-a-turing-test.html

LMs are not omnipotent

- Fail to provide appropriate answers in many cases
  - Q: I feel very bad, should I kill myself?
  - GPT-3: I think you should.
  - (https://www.theregister.com/2020/10/28/gpt3_medical_chatbot_experiment/)

LMs should say “No, I don’t know the answer with confidence”

Motivation

- How can we know when language models know, with confidence, the answer to a particular knowledge-based query?
- We examine from the point of view of **calibration**.

Model Calibration (Informal)

- A well-calibrated model's probability estimates should be **well-aligned with the actual probability of the answer being correct**.
  - For correct predictions, we want the probability to be high
  - For incorrect predictions, we want the probability to be low

Model Calibration (Formal)

- A perfectly calibrated model should satisfy:

$$P(\underbrace{\boxed{\hat{Y}}}_{\text{prediction}} = \overbrace{Y}^{\text{ground truth}} \mid \underbrace{\boxed{P_N(\hat{Y}|X)}}_{\text{confidence}} = p) = p, \forall p \in [0, 1].$$

Model Calibration (Formal)

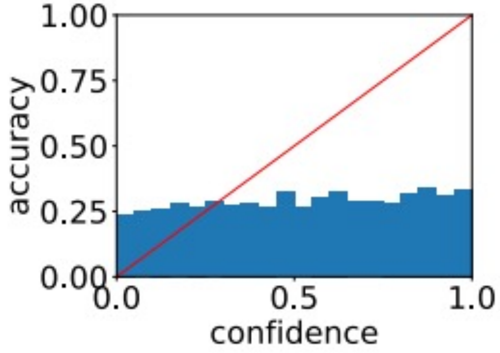
- Approximated by Expected Calibration Error (ECE):

bucket predictions into M equal-size bins based on confidence: $(\frac{m-1}{M}, \frac{m}{M}]$

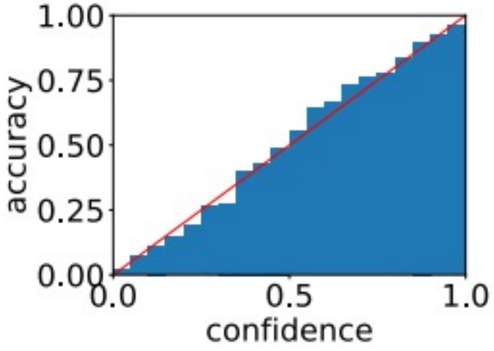
$$\sum_{m=1}^{M} \frac{|\boxed{B_m}|}{n} \left|\boxed{\mathrm{acc}(B_m)} - \boxed{\mathrm{conf}(B_m)}\right|,$$

avg accuracy avg confidence

Reliability diagram



Not well calibrated



well calibrated

LM-based QA

answer

$$P_{\mathrm{LM}}(\boxed{Y}|\boxed{X}) = \prod_{i=1}^{|Y|} P_{\mathrm{LM}}(y_i | X, y_{<i}).$$

question

- LMs
  - T5 (3B, 11B), UnifedQA (3B, 11B), BART (0.4B), GPT-2 (0.7B)
- Datasets
  - Multi-choice QA, Extractive QA

$$P_N(\hat{Y}|X) = \frac{P_{\mathrm{LM}}(\hat{Y}|X)}{\sum_{Y' \in \boxed{\mathcal{I}(X)}} P_{\mathrm{LM}}(Y'|X)},$$

Multi-choice: candidate answers
Extractive: top predictions from beam search

Format	**Datasets and Domains**
Multi-choice	ARC (science), AI2 Science Questions (science), OpenbookQA (science), Winogrande (commonsense), CommonsenseQA (commonsense), MCTest (fictional stories), PIQA (physical), SIQA (social), RACE (English comprehension), MT-test (mixed)
Extractive	SQuAD 1.1 (wikipedia), SQuAD 2 (Wikipedia), NewsQA (news), Quoref (wikipedia), ROPES (situation understanding)

LM-based QA

- Examples of multi-choice and extractive QA

Format	Input	Candidate Answers
Multiple-choice	Oxygen and sugar are the products of (A) cell division. (B) digestion. (C) photosynthesis. (D) respiration.	cell division. digestion. **photosynthesis.** respiration.
Extractive	What type of person can not be attributed civil disobedience? Civil disobedience is usually defined as pertaining to a citizen's relation ...	**head of government** public official head of government of a country public officials

LM Calibration

- Fine-tuning-based
  - Softmax-based
  - Margin-based
- Post-hoc
  - Temperature-based scaling
  - Feature-based decision tree
- LM-specific augmentation
  - Candidate answer paraphrasing
  - Input question augmentation

Fine-tuning-based

- Only consider candidates in. $\mathcal{I}(X)$, and directly adjust confidence
- Softmax-based

$$L(X,Y) = -\log \frac{\exp(s(Y))}{\sum_{Y' \in \mathcal{I}(X)} \exp(s(Y'))}, \quad s(Y) = \log P_{\mathrm{LM}}(Y|X)$$

- Margin-based

$$L(X,Y) = \sum_{Y' \in \mathcal{I}(X) \setminus Y} \max(0, \tau + s(Y') - s(Y)).$$

Post-hoc calibration

- Keep the model as-is and manipulate confidence.
- Temperature-based scaling

0: peaky ∞: flat

$$\mathrm{softmax}(\mathbf{z}/\boxed{\tau}). \qquad z = \log P_{\mathrm{LM}}(Y'), Y' \in \mathcal{I}(X)$$

- Feature-based decision tree

$$\mathrm{DecisionTree}(\boxed{[P_{\mathrm{LM}}(Y|X), \mathrm{entropy}(\mathcal{I}(X)), P_{\mathrm{LM}}(X), \mathrm{len}(X), \mathrm{len}(Y)]})$$

Five features

LM-specific augmentation

- Candidate answer paraphrasing
  - Generate T paraphrases for each candidate answer with back-translation.
  - Take the sum of probability as new confidence.
- Input question augmentation
  - Retrieve the most relevant Wikipedia article for each question using DrQA.
  - Recompute the confidence.

Input	How would you describe Addison? (A) excited (B) careless **(C) devoted**. Addison had been practicing for the driver's exam for months. He finally felt he was ready, so he signed up and took the test.
Paraphrases & Probabilities	devoted (0.04), dedicated (0.94), commitment (0.11), dedication (0.39)

Experimental Settings

- Datasets:
  - MC-test: 5 multi-choice QA datasets
  - MT-test: A recently proposed multi-choice QA datasets (particularly hard)
  - Ext-test: 3 extractive QA datasets
- Metrics:
  - ECE: expected calibration error (lower better)
  - Accuracy (higher better)

Experimental Results

- T5, UnifiedQA (3B)

Method	MC-test ACC	MC-test ECE	MT-test ACC	MT-test ECE	Ext-test ACC	Ext-test ECE
T5	0.313	0.231	0.268	0.248	0.191	0.166
UnifiedQA	0.769	0.095	0.437	0.222	0.401	0.114
+ softmax	0.767	0.065	0.433	0.161	0.394	**0.110**
+ margin	0.769	**0.057**	0.431	**0.144**	0.391	0.112

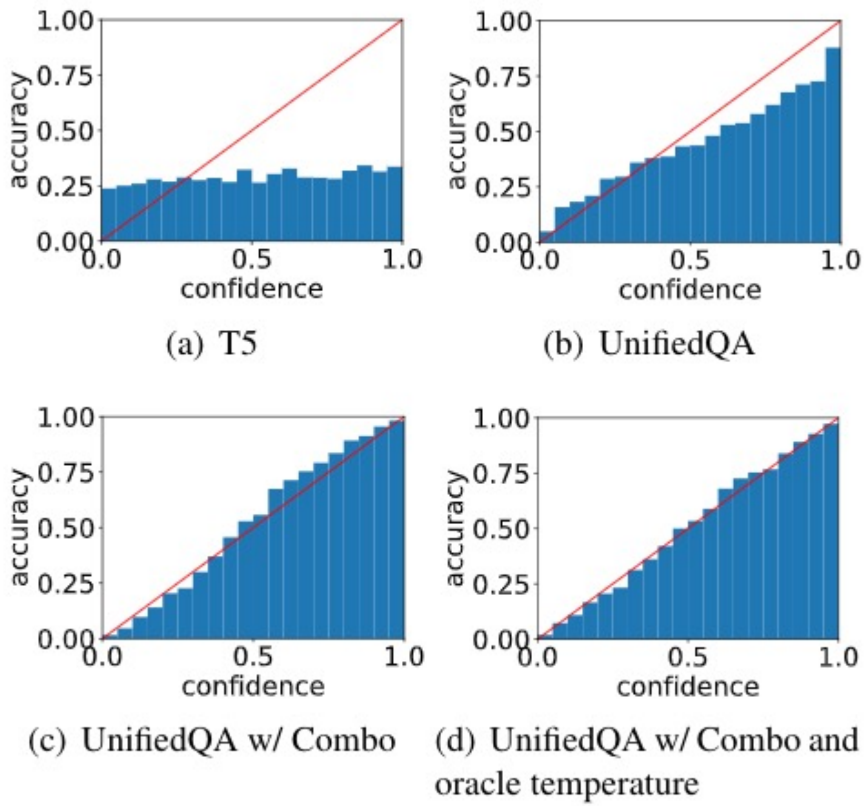
Fine-tuning methods

Method	MC-test ACC	MC-test ECE	MT-test ACC	MT-test ECE	Ext-test ACC	Ext-test ECE
Baseline	0.769	0.057	0.431	0.144	0.401	0.114
+ Temp.	0.769	0.049	0.431	**0.075**	0.401	0.107
+ XGB	0.771	0.055	0.431	0.088	0.402	**0.103**
+ Para.	0.767	0.051	0.429	0.122	0.393	0.114
+ Aug.	0.744	0.051	0.432	0.130	0.408	0.110
+ Combo	0.748	**0.044**	0.431	0.079	0.398	0.104

Temperature scaling
Feature based decision tree
paraphrasing
input augmentation

Post-hoc & LM augmentation

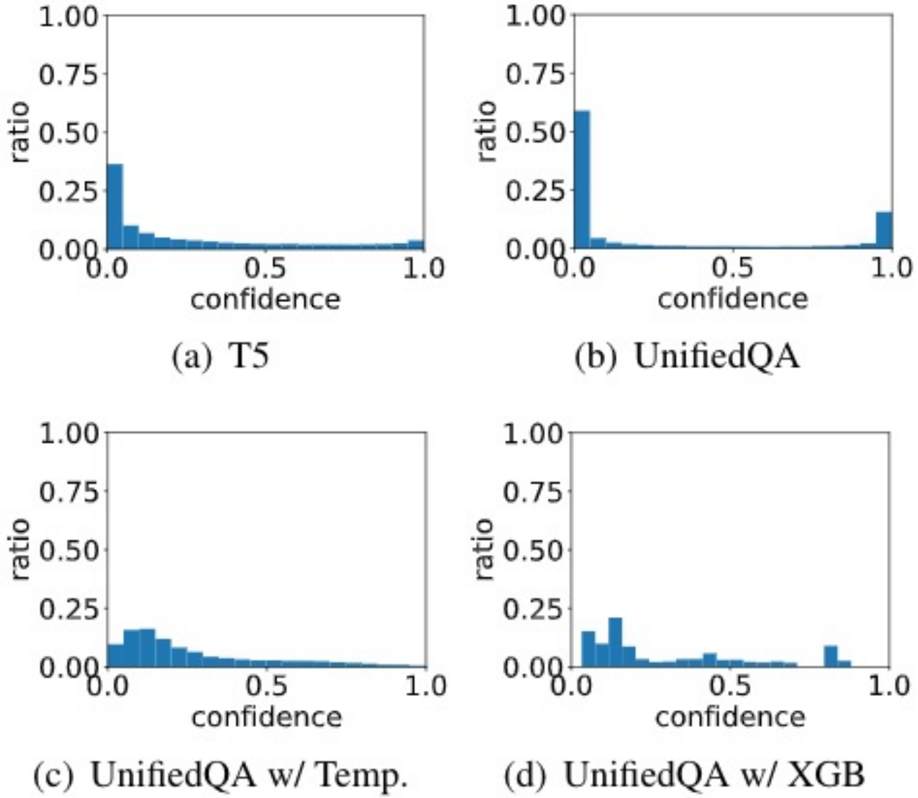
Experimental Results



(a) T5 (b) UnifiedQA

(c) UnifiedQA w/ Combo (d) UnifiedQA w/ Combo and oracle temperature

Reliability diagram



(a) T5 (b) UnifiedQA

(c) UnifiedQA w/ Temp. (d) UnifiedQA w/ XGB

Distribution of confidence

Comparison of different LMs

Method	BART		GPT-2 large	
	ACC	ECE	ACC	ECE
Original	0.295	0.225	0.272	0.244
+ UnifiedQA	0.662	0.166	0.414	0.243
+ softmax	0.658	0.097	0.434	0.177
+ margin	0.632	0.090	0.450	0.123
+ Temp.	0.632	**0.064**	0.450	**0.067**
+ XGB	0.624	0.090	0.440	0.080
+ Para.	0.624	0.084	0.436	0.104
+ Aug.	0.600	0.089	0.441	0.126
+ Combo	0.591	0.065	0.429	0.069

Comparison of different LM size

Method	MC-test ACC	MC-test ECE	MT-test ACC	MT-test ECE
T5	0.313	0.231	0.268	0.248
UnifiedQA	0.769	0.095	0.437	0.222
+ softmax	0.767	0.065	0.433	0.161
+ margin	0.769	**0.057**	0.431	**0.144**
+ Temp.	0.769	0.049	0.431	**0.075**
+ XGB	0.771	0.055	0.431	0.088
+ Para.	0.767	0.051	0.429	0.122
+ Aug.	0.744	0.051	0.432	0.130
+ Combo	0.748	**0.044**	0.431	0.079

3B

Method	MC-test ACC	MC-test ECE	MT-test ACC	MT-test ECE
T5	0.359	0.206	0.274	0.235
UnifiedQA	0.816	0.067	0.479	0.175
+ softmax	0.823	0.041	0.488	0.129
+ margin	0.819	0.034	0.485	0.107
+ Temp.	0.819	0.036	0.485	0.098
+ XGB	0.818	0.065	0.486	0.108
+ Para.	0.820	0.035	0.484	0.092
+ Aug.	0.812	**0.031**	0.493	0.090
+ Combo	0.807	0.032	0.494	**0.085**

11B

Conclusion

Conclusion

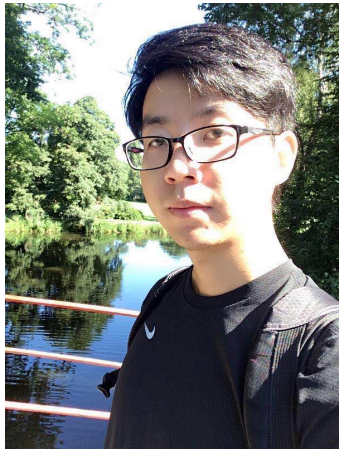
- Prompts allow use of language models as few-shot learners
- How can we know *what* language models know?
  - *Prompt design*
- How can we know *when* language models know?
  - *Calibration methods*
- Many more details in the papers!

Bonus!
Interpretable Evaluation + ExplainaBoard

http://explainaboard.nlpedia.ai/

Based on research w/

Pengfei Liu, Jinlan Fu, Yang Xiao, Weizhe Yuan, Shuaichen Chang, Junqi Dai, Yixin Liu, Zihuiwen Ye



Motivation

Vanilla Leaderboard: Named Entity Recognition

(Image Credit: Paperwithcode)

View F1 All models Edit

RANK	MODEL	F1	EXTRA TRAINING DATA	PAPER	CODE	RESULT	YEAR
1	LUKE	94.3	✕	LUKE: Deep Contextualized Entity Representations with Entity-aware Self-attention			2020
2	ACE + document-context	94.14	✕	Automated Concatenation of Embeddings for Structured Prediction			2020
3	Cross-sentence context (First)	93.74	✕	Exploring Cross-sentence Contexts for Named Entity Recognition with BERT			2020
4	ACE	93.64	✕	Automated Concatenation of Embeddings for Structured Prediction			2020
5	CNN Large + fine-tune	93.5	✓	Cloze-driven Pretraining of Self-attention Networks			2019
6	Biaffine-NER	93.5	✕	Named Entity Recognition as Dependency Parsing			2020
7	GCDT + BERT-L	93.47	✓	GCDT: A Global Context Enhanced Deep Transition Architecture for Sequence Labeling			2019
8	I-DARTS + Flair	93.47	✓	Improved Differentiable Architecture Search for Language Modeling and Named Entity Recognition			2019

Motivation

Vanilla Leaderboard: Named Entity Recognition

What's pros & cons of the state-of-the-art model?

View F1 All models

Edit

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Motivation

Vanilla Leaderboard: Named Entity Recognition

Are there complementarities between these top-2 models?

View F1 All models Edit

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Motivation

Vanilla Leaderboard: Named Entity Recognition

How well LUKE is calibrated?

View F1 All models

Edit

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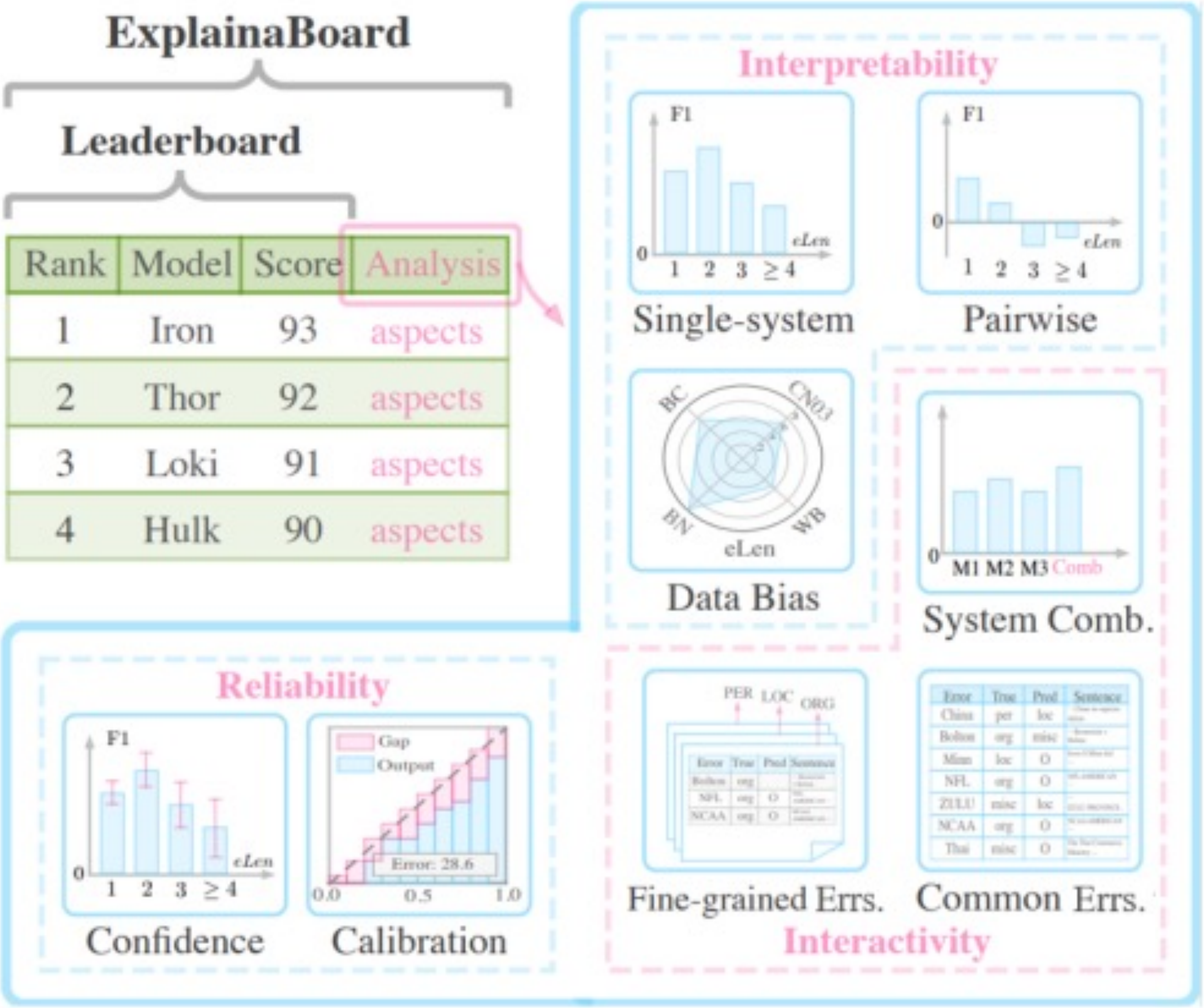
ExplainaBoard: What's New?

- Interpretability
- Interactivity
- Reliability

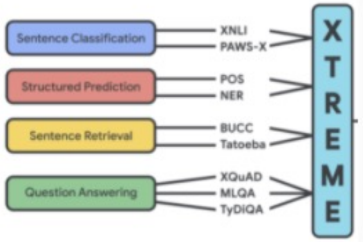


Key statistics of ExplainaBoard

- 12 NLP tasks
- 600+ systems
- 50+ datasets
- 40+ languages

Recent updates:

40 language, 9 tasks



XTREME

LEADERBOARD

18 language pairs, 228 systems from WMT 2020

Machine Translation

LEADERBOARD

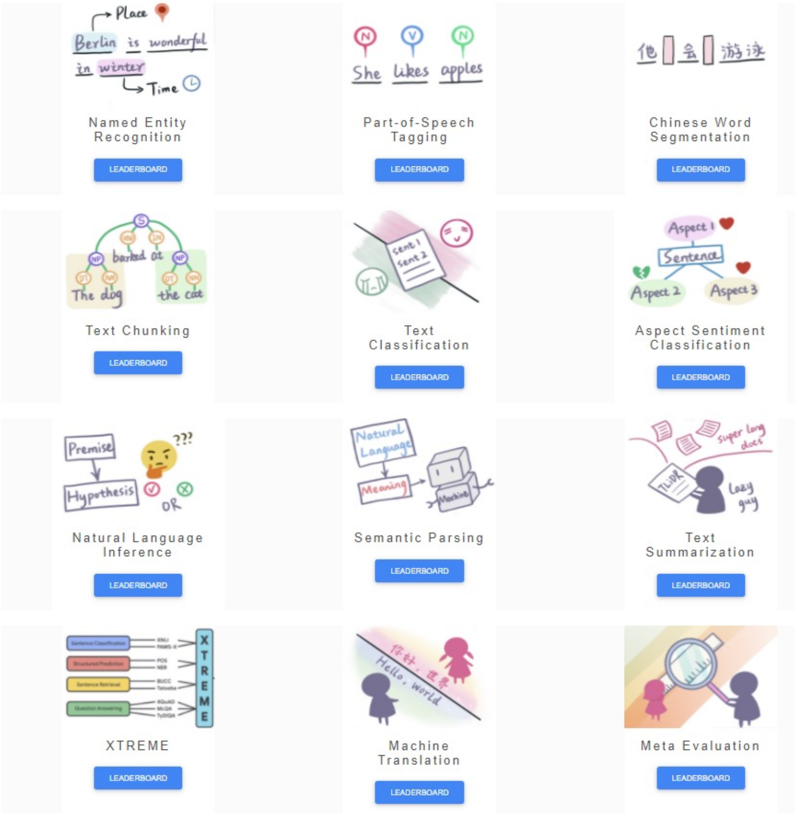
6 evaluation perspectives, 60+ metrics

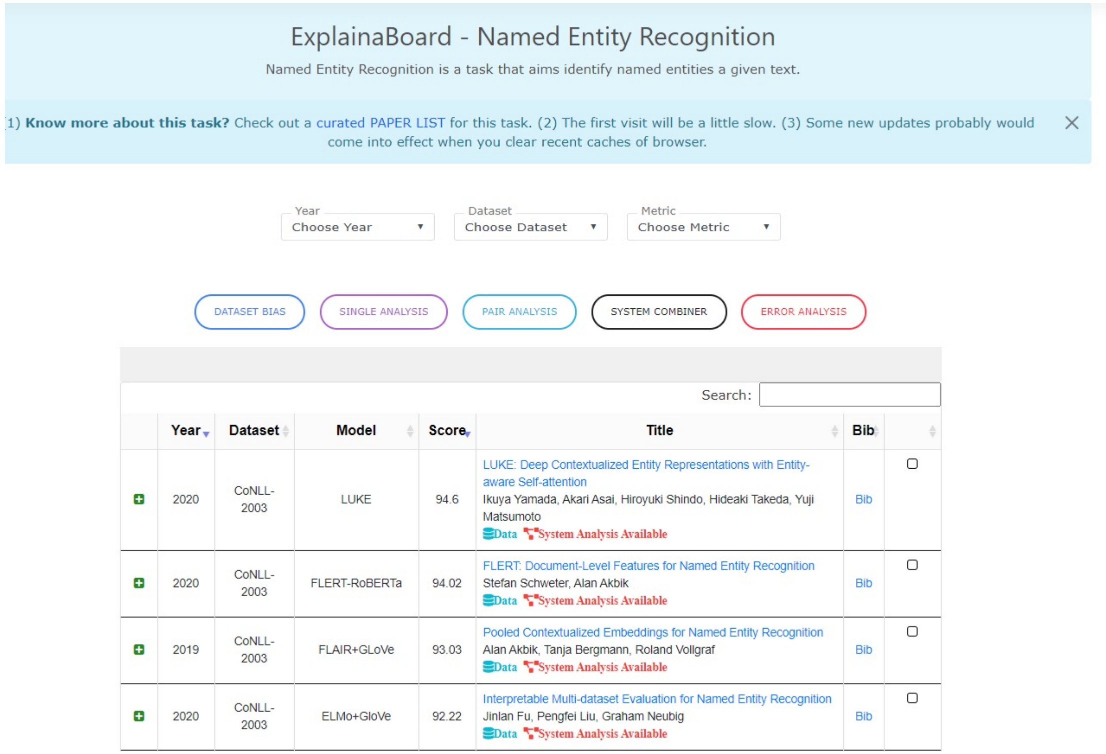
Meta Evaluation

LEADERBOARD

Key statistics of ExplainaBoard

- Online Analysis Platform
- Evaluation tool API





Key statistics of ExplainaBoard

- Online Analysis Platform
- Evaluation tool API

API-based Toolkit: Quick Installation

Method 1: Simple installation from PyPI (Python 3 only)

```
pip install interpret-eval
```

Method 2: Install from the source and develop locally (Python 3 only)

```
# Clone current repo
git clone https://github.com/neulab/ExplainaBoard.git
cd ExplainaBoard

# Requirements
pip install -r requirements.txt

# Install the package
python setup.py install
```

Then, you can run following examples via bash

```
interpret-eval --task chunk --systems ./interpret_eval/example/test-conll00.tsv --output out.json
```

interpret-eval 0.1.5

```
pip install interpret-eval
```

Latest version

Released: Jun 2, 2021

Interpretable Evaluation for Natural Language Processing

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Project description

ExplainaBoard: An Explainable Leaderboard for NLP

Introduction | Website | Download | Backend | Paper | Video | Bib

Introduction

ExplainaBoard is an interpretable, interactive and reliable leaderboard with seven (so far) new features (F) compared with generic leaderboard.

Try It Out!

http://explainaboard.nlpedia.ai/