PAWS-X: A Cross-lingual Adversarial Dataset for Paraphrase Identification

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About the Author

- Google Research
- <u>Yinfei Yang</u>, <u>Yuan Zhang</u>, Chris Tar, Jason Baldridge
- Google AI blog

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- Why PAWS-X?
- What is PAWS-X?

- Why PAWS-X?
- What is PAWS-X?

Method

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Conclusion

- Adversarial examples have effectively highlighted the deficiencies of state-of-the-art models for many natural language processing tasks
- PAWS, which has adversarial paraphrase identification pairs with high lexical overlap.
 - E.g. flights from New York to Florida vs flights from Florida to New York
- Research on adversarial examples has generally shown that augmenting training data with good adversarial examples can boost performance for some models



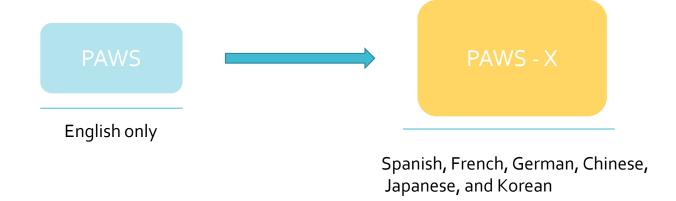
- Why PAWS-X?
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- Most previous work focuses only on English despite the fact that the problems highlighted by adversarial examples are shared by other languages.
 - E.g. Multi3oK , Opusparcus

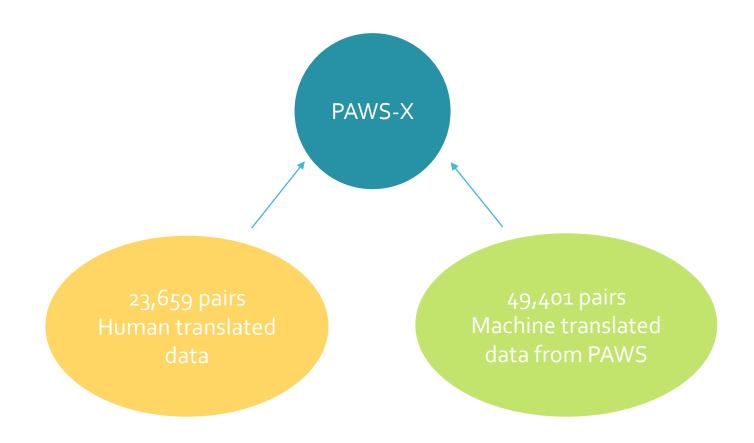


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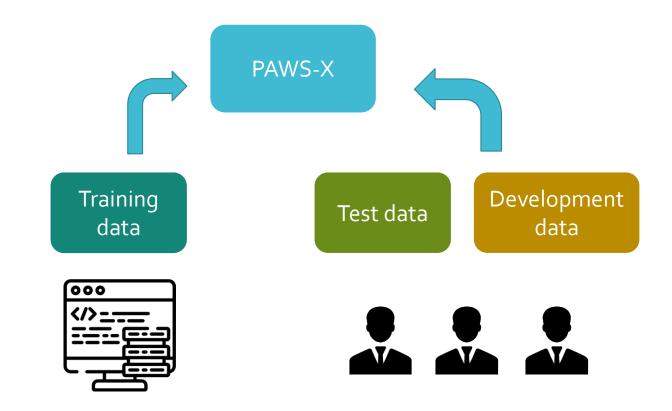


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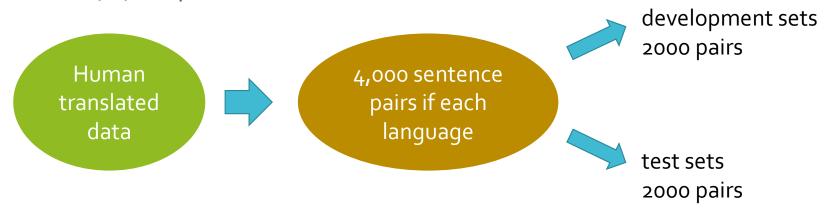
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Translating Evaluation Sets

- Obtaining human translations on a random sample of 4,000 sentence pairs from the PAWS development set for each of the six languages
- A randomly sampled subset is presented and validated by a second worker. The final delivery is guaranteed to have less than 5% word level error rate.
- The sampled 4,000 pairs are split into new development and test sets, 2,000 pairs for each.



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| | fr | es | de | zh | ja | ko |
|-----|-------|-------|-------|-------|-------|-------|
| dev | 1,992 | 1,962 | 1,932 | 1,984 | 1,980 | 1,965 |
| | 1,985 | | | | | |

Table 2: Examples translated per language.

- Some sentences could not be translated. Table 2 shows the final counts translated to each language.
 - Incompleteness, ambiguities
 - likely from the Adversarial generation process when creating PAWS
 - < 2%
- Original PAWS labels (paraphrase or not paraphrase) are mapped to the translations. Positive pairs account for 44.0% of development sets and 45.4% of test respectively—close to the PAWS label distribution.
- Entity mention problem

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PAWS-X: Probe models' ability to capture structure and context in a multilingual setting.

BOW encoder with COS similarity

- Unigram to bigram token
- Cosine value > 0.5 as a paraphrase

ESIM(Enhanced Sequential Inference Model)

- BiLSTM
- feed-forward layer

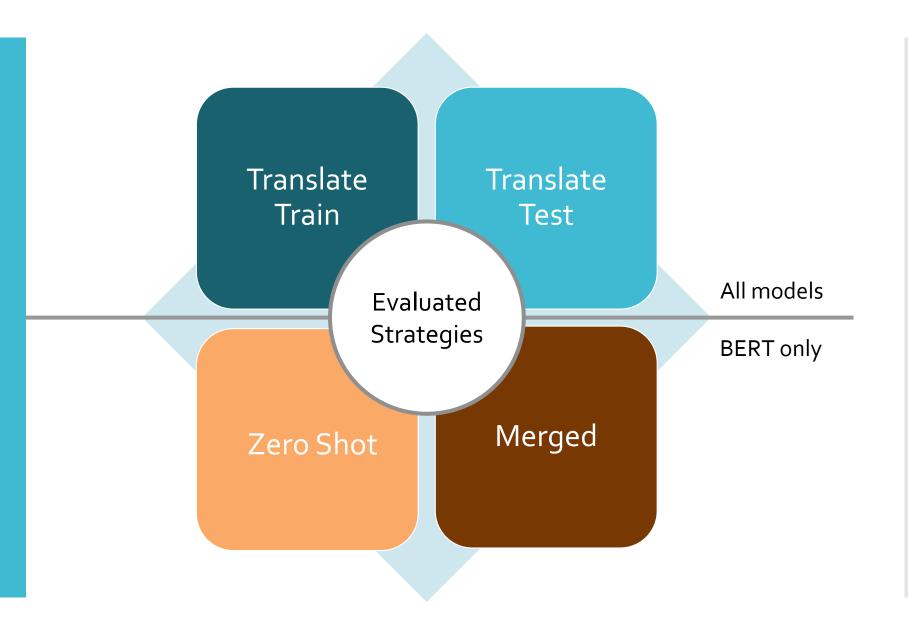
BERT(Bidirectional Encoder Representations from Transformers)

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Translate Train:

• English training data is machine-translated into each target language to provide data to train each model.

Translate Test:

 Train a model using the English training data, and machine-translate all test examples to English for evaluation.

· Zero Shot:

 The model is trained on the <u>PAWS English</u> training data, and then directly evaluated on all others. Machine translation is not involved in this strategy.

Merged:

• <u>Train a multilingual model on all languages</u>, including the original English pairs and machine-translated data in all other languages.

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• BERT:

 Latest public multilingual BERT base model with 12 layers2 and apply the default fine-tuning strategy with batch size 32 and learning rate 1e-5.

BOW and ESIM:

 using their own implementations and 300 dimensional multilingual word embeddings from fastText.

Two metrics :

- Classification accuracy
- Area-under-curve scores of precision-recall curves (<u>AUC-PR</u>)

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| Method | Accuracy | | | | | AUC-PR | | | | | | | | |
|-----------------|----------|------|------|------|------|--------|------|------|------|------|------|------|------|------|
| Method | en | fr | es | de | zh | ja | ko | en | fr | es | de | zh | ja | ko |
| BOW | | | | | | | | | | | | | | |
| Translate Train | 55.8 | 51.7 | 47.9 | 50.2 | 54.5 | 55.1 | 56.7 | 41.1 | 48.9 | 46.8 | 46.4 | 50.0 | 48.7 | 49.3 |
| Translate Test | _ | 54.9 | 54.7 | 55.2 | 55.3 | 55.9 | 55.2 | _ | 46.3 | 45.5 | 45.8 | 50.9 | 46.8 | 48.5 |
| ESIM | | | | | | | | | | | | | | |
| Translate Train | 67.2 | 66.2 | 66.0 | 63.7 | 60.3 | 59.6 | 54.2 | 69.6 | 67.0 | 64.2 | 59.2 | 58.2 | 56.3 | 50.5 |
| Translate Test | _ | 66.2 | 66.3 | 66.0 | 62.0 | 62.3 | 60.6 | _ | 68.4 | 69.5 | 68.2 | 62.3 | 61.8 | 60.3 |
| BERT | | | | | | | | | | | | | | |
| Translate Train | 93.5 | 89.3 | 89.0 | 85.3 | 82.3 | 79.2 | 79.9 | 97.1 | 93.6 | 92.4 | 92.0 | 87.4 | 81.4 | 82.4 |
| Translate Test | _ | 88.7 | 89.3 | 88.4 | 79.3 | 75.3 | 72.6 | _ | 93.8 | 93.1 | 92.9 | 85.1 | 80.9 | 80.1 |
| Zero shot | _ | 85.2 | 86.0 | 82.2 | 75.8 | 70.5 | 71.7 | _ | 91.0 | 90.5 | 89.4 | 79.6 | 72.7 | 75.5 |
| Merged | 93.8 | 90.8 | 90.7 | 89.2 | 85.4 | 83.1 | 83.9 | 96.5 | 94.0 | 92.9 | 92.9 | 88.9 | 86.0 | 86.3 |

Table 4: Accuracy (%) and AUC-PR (%) of each approach. Best numbers in each column are marked in bold.

| | Averaged | | | | | |
|-----------------|--|---|--|--|--|--|
| | Accuracy | AUC-PR | | | | |
| Translate Train | 52.7 | 48.4 | | | | |
| Translate Test | 55.2 | 47.3 | | | | |
| Translate Train | 61.7 | 59.2 | | | | |
| Translate Test | 63.9 | 65.1 | | | | |
| Translate Train | 84.2 | 88.2 | | | | |
| Translate Test | 82.3 | 87.6 | | | | |
| Zero Shot | 78.6 | 83.1 | | | | |
| Merged | 87.2 | 90.2 | | | | |
| | Translate Test Translate Train Translate Test Translate Train Translate Train Translate Test Zero Shot | Translate Train 52.7 Translate Test 55.2 Translate Train 61.7 Translate Test 63.9 Translate Train 84.2 Translate Test 82.3 Zero Shot 78.6 | | | | |

Table 5: Average Accuracy (%) and AUC-PR (%) over the six languages.

- Model Comparisons
- Training/Evaluation Strategies
- Language Difference



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Our experimental results showed that PAWS-X effectively measures sensitivity of models to word order and the efficacy of cross-lingual learning approaches.

It also leaves considerable headroom as a new challenging benchmark to drive multilingual research on the problem of paraphrase identification.

The PAWS-X dataset, including both the new human translated pairs and the machine translated examples, is available for download at https://github.com/google-research-datasets/paws.

